The modeling of response indicators of integrated water resources management with artificial neural networks in the Saf-Saf river basin (N-E of Algeria)

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ملخص
يهدف هذا البحث إلى تحديد التدخل الأهم في سياق الاستجابة التقنية والسياسية تحت إطار التسيير المندمج للموارد المائية في حوض واد الصفصاف، التي يتميز بلوتفاع معدل النمو السكاني وتطور القطاع الاقتصادي بما في ذلك الصناعة والزراعة. في هذه الدراسة، تم استخدام الشبكة العصبية الاصطناع(NNA) لوضع نموذج والتنبؤ بالعلاقات الحاصلة بين متغيرات الاستجابة وتعبئة الموارد المائية في حوض صاف صرلف. ولقد تم جمع المعطيات الفعلية من ثلاثين (30) بلدية في الحوض للسنة المرجعية 2010. إن النتائج تشير إلى أن "nortpecreP" متعدد الطبقات (PLM) هو النموذج الأكثر فاعلية في تحديد متغير الاستجابة الأكثر تأثيرا في تعبئة الموارد المائية والتدخل من أجل حل المشاكل المترتبة. حيث أن معايرة النموذج جيدة مع معامل الارتباط يفوق 96٪ للمراحل الثلاث: التعلم، والتحقق والاختبار. هذا النموذج يهدف إلى ربط تعبئة الموارد المائية ومتغيرات الاستجابة مع مقاربة التسيير المتكامل للموارد المائية.

الكلمات المفتاحية : *حوض واد الصفصاف - متغيرات الاستجابة - تعبئة الموارد المائية – التسيير المندمج للموارد المائية - شبكة .*

Résumé
Cette étude a pour but de déterminer l'intervention la plus importante dans la catégorie de réponse politique et technique dans le cadre de la Gestion Intégrée des Ressources en Eau dans le bassin versant de l'oued Saf-Saf, qui se caractérise par une forte croissance démographique et une évolution du secteur économique incluant l'industrie et l'agriculture. Dans ce travail, le Réseau de Neurone Artificiel a été utilisé pour la modélisation et la prévision des relations existantes entre les variables de réponse et la mobilisation des ressources en eau dans le bassin versant de l'oued Saf-Saf. Les données réelles sont collectées à partir de trente (30) municipalités du bassin versant pour l'année de référence 2010. Les résultats indiquent que le Perceptron multicouches est le modèle le plus performant pour définir la variable de réponse la plus influente sur la mobilisation des ressources en eau et d'intervenir pour résoudre les problèmes éventuels. Le calage du modèle est bon avec un coefficient de corrélation supérieur à 96% pour les trois phases : l'apprentissage, la validation et le test. Le modèle vise à relier la mobilisation des ressources en eau et les variables de réponse avec l'approche de la Gestion Intégrée des Ressources en Eau.

Mots clés *: Bassin Versant de l'oued Saf-Saf - Variables de réponse – Mobilisation des ressources en eau – Gestion Intégrée des ressources en Eau – Perceptron multicouches.*

Abstract
This study focuses on determining the most important intervention in technical and managerial policy response category of Integrated Water Resources Management in the Saf-Saf river basin characterized by the fast growing demand of populations and economic sectors including industry and agriculture. The artificial neural networks models were used to model and predict the relationship between water resources mobilization WRM and response variables in the Saf-Saf river basin, where real data were collected from thirty municipalities for reference year 2010.The results indicate that the feed forward multilayer perceptron models with back propagation are useful tools to define and prioritize the most effective response variable on water resources mobilization to intervene and solve water problems. The model evaluation shows that the correlation coefficients are more than 96% for training, verification and testing data. The model aims at linking the water resources mobilization and response variables with the objective to strengthen the Integrated Water Resources Management approach.

Key words*: Saf-Saf river basin - Response variables - Water Resources Mobilization - Integrated Water Resources Management - Multilayer perceptron*

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1. INTRODUCTION

Integrated Water Resources Management is a systematic process for sustainable development, allocation, and monitoring of water resources viewed as both an economic, environmental and a social good. The new conceptual model interprets the three systems through five categories including socio-economic aspects, pollution, impact, state of water quality and the institutional response presents the efforts of the administration and policy making level.

To assist water planners and managers to gain adequate knowledge and understanding of the relationships between the response variables and water resources mobilization, there is a need to use a proper methodology to define the effective response variable influencing the attractiveness of water resources mobilization.

In recent years, the artificial neural networks (ANN) models have been successfully applied in hydrological processes, such as rainfall–runoff modelling [1] and rainfall forecasting [2] and in water resources context, the ANN has been used for water quality parameters [3], forecasting of water demand [4], stream flow forecasting [5], prediction of rainfall-runoff relationship [6, 7] and coastal aquifer management [8], streamflow modelling [9] and reservoir operation problems [10]. Hornik *et al.* [10] showed how ANNs could be applied to different problems in civil engineering, while Maier and Dandy [11] reviewed several papers dealing with the use of neural network models for the prediction and forecasting of water resources variables.

A back propagation feed forward multilayer perceptron (MLP) with sigmoidal-type transfer functions is the most popular neural network architecture due to its high performance compared to the other networks [12]. This paper introduces the back propagation feed forward Multilayer Perceptron and Radial Basis Function (RBF).

This study aims at establishing a modelling relationship between water resources mobilization and response variables, and characterize their priorities.

2. METHODOLOGY

2.1 Study area and data description

The Saf-Saf river basin is situated in the North East of Algeria (Fig. 1). It is bordered by the Guebli river basin from the West, the upstream of Seybouse river basin from the South, Kebir West river basin from the East; and finally Mediterranean Sea from the North. The total area of the Saf-Saf river basin is 1158 km^2 and covers 30 municipalities.

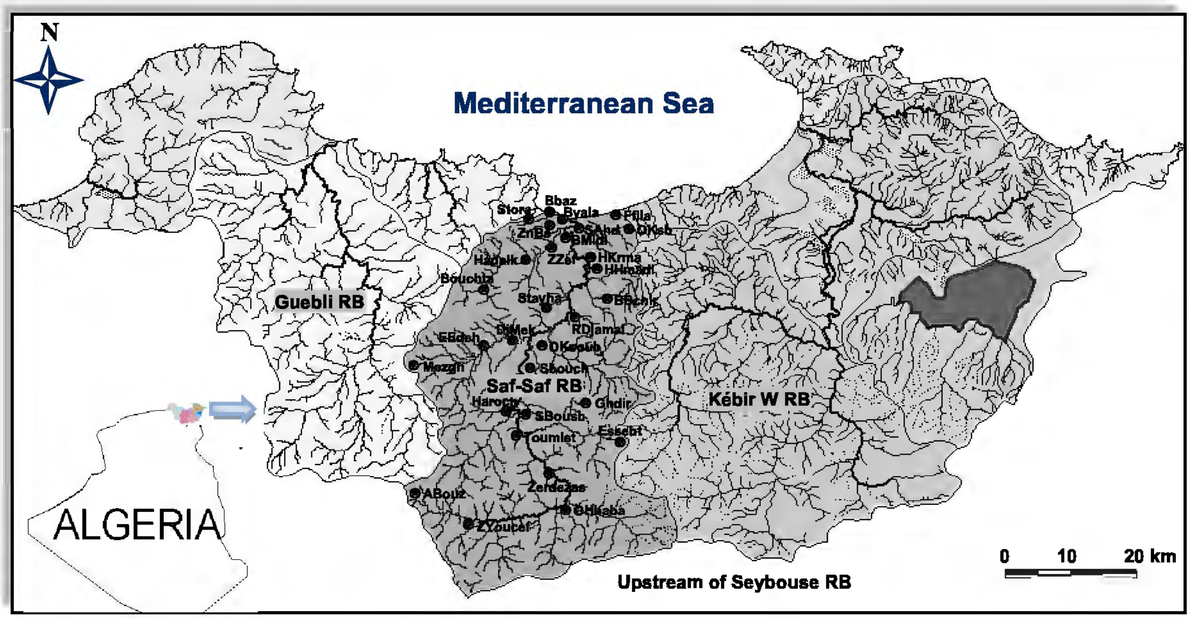

Figure 1. Geographical Projection of Saf-Saf River Basin

Water resources in the study area are vulnerable to the fast growing demand of urban and rural populations, demand of economic sectors including agriculture, industry and public institutions. The population is estimated at 425068 capita (in 2010); domestic water supply ranges from 75 to 150 liters per capita per day ($l.c^{-1}.d^{-1}$). The industry is concentrated in the downstream part of river basin, it consummate 7.1 $hm^3.y^{-1}$ and finally, the important agriculture is located along the Valley of Saf-Saf river basin with consumption of water estimated at 24.45 $hm^3.year^{-1}$.

The data of Water Resources Mobilization (WRM) and response variables were applied to create the ANN model using the software package of STATISTICA 8. The data base used are collected and compiled by many services from the thirty municipalities as independent data sets (each case is independent) for the reference year 2010. The response variables were:

- Storm Water Harvesting (StoWHa) represents collection of rainfall using check dams. It is measured by million cubic meters per year ($hm^{-3}.y^{-1}$).
- Importation of Water (ImpW) represents the amount of water transferred from one municipality to another. It is measured by million cubic meters ($hm^{-3}.y^{-1}$).
- Efficiency in Water Irrigation (EfWIrrig) refers to the agricultural water consumption as a percentage of the water production for agriculture use.
- Efficiency in Urban Water Supply Network (EfUWSN) refers to the municipal water consumption as a proportion of the water production from the municipal water resources.
  Efficiency= consumption/production
- Efficiency of Information System (EfInS) refers to the level of existing information system including human resources, equipment, and software as a ratio to the required water information system to better manage the water resources issue.
- Water Awareness and education (WAwar) represents the number of people participated in the educational campaigns on the rational use of water. These campaigns were arranged by the institutions of water management and education ministry, estimated by number.
- Sea Water Desalination (SWD) indicates the amounts of desalinated seawater used by the population. It is measured in million cubic meters ($hm^{-3}.y^{-1}$).

The variables representing response category are considered as the possible inputs variables whilst the target output variable is the WRM measured by $hm^3.year^{-1}$.

2.2 Criteria of evaluation

A variety of verification criteria that could be used for the evaluation and intercomparison of different models was proposed by the World Meteorological Organization (WMO). They fall into two groups: graphical indicators and numerical performance indicators of the several numerical indicators [13], suitable ones for the present study are chosen. These are the sum of square error (RMSE) and the correlation coefficients (R^2) [14], given by:

$$RMSE = \sum_{i=1}^{N} (Qi - \hat{Q}i)^2 \qquad (1)$$

$$R^2 = \left[\frac{\sum_{i=1}^{N} (Qi - \overline{Qi})(\hat{Q}i - \overline{\hat{Q}i})}{\sqrt{\sum_{i=1}^{N} (Qi - \overline{Qi})^2} \sqrt{\sum_{i=1}^{N} (\hat{Q}i - \overline{\hat{Q}i})^2}} \right]^2 \qquad (2)$$

Where Qi is the observed water resources mobilization value; $\hat{Q}i$ is the predicted water resources mobilization value; $\overline{Q}i$ is the mean value of Qi values; $\overline{\hat{Q}i}$ is the mean value of $\hat{Q}i$ values; N is the total number of data sets.

The RMSE gives a quantitative indication for the network error. It measures the deviation of the predicted values from the corresponding observed values of target output which refers to the prediction accuracy [15, 16].

Besides, the RMSE was used to compare the performance of MLP with other common types of ANNs like RBF.

The R^2 value is an indicator of how well the network fits the data and accounts for the variability with the variables specified in the network. A value of R^2 above 90% refers to a very satisfactory model performance. Values range between 80-90% indicates unsatisfactory model [2, 17]. The ideal value for RMSE is zero and for R^2 is unity.

2.3 Creating the network

ANN models are mathematical tools, capable of modeling extremely complex functions and wide spectrum of challenging problems [4]. They constitute a computational approach inspired by the human nervous system. The processing units of an artificial neural network are called neurons, which are arranged into layers. Neurons between layers are connected by links of variable weights. The most popular neural network model is the MLP. The MLP is a layered feed forward network, which is typically trained with BFGS back propagation (Broyden Fletcher Goldfarb Shanno Quasi-Newton) [18 - 21] and SCG back propagation (Scaled Conjugate Gradient). The number of neurons in a hidden layer is decided after training and testing. Multi layered network, trained by back propagation [22] are currently the most popular and proven [23] and have been used in this study. Training of ANN consists of showing example inputs and target outputs to the network and iteratively adjusting internal parameters based on performance measures. The MLP is simple, robust, and very powerful in pattern recognition, classification, and mapping. MLP is capable of approximating any measurable function from one finite dimensional space to another within a desired degree of accuracy [10].

In this work, a feed forward Multilayer Perceptron network with a back propagation algorithm was chosen as a model of the system.

The network processes are an input vector consisting of possible variables including StoWHa, ImpW, EfWIrrig, EfUWSN, EfInS, WAwar and SWD. This input vector generates an output vector which is WRM. The MLP network can be represented by the following compact form:

{WRM}= ANN [StoWHa, ImpW, EfWIrrig, EfUWSN, EfInS, WAwar, SWD]

A schematic diagram of neural network is given in figure 2.

It shows a typical feed forward structure with signals flow from input nodes, forward through hidden nodes, eventually reaching the output node. The input layer is not really neural at all; these nodes simply serve to introduce the standardized values of the input variables to the neighbouring hidden layer without any transformation. The hidden and output layer nodes are each connected to all of the nodes in the preceding layer. However, the nodes in each layer are not connected to each other. A numeric weight is associated with each of the inter-node connections. Weight of Wij represents the strength of connections of nodes between input and hidden layer while Wjk represents the strength of connections of nodes between hidden and output layers.

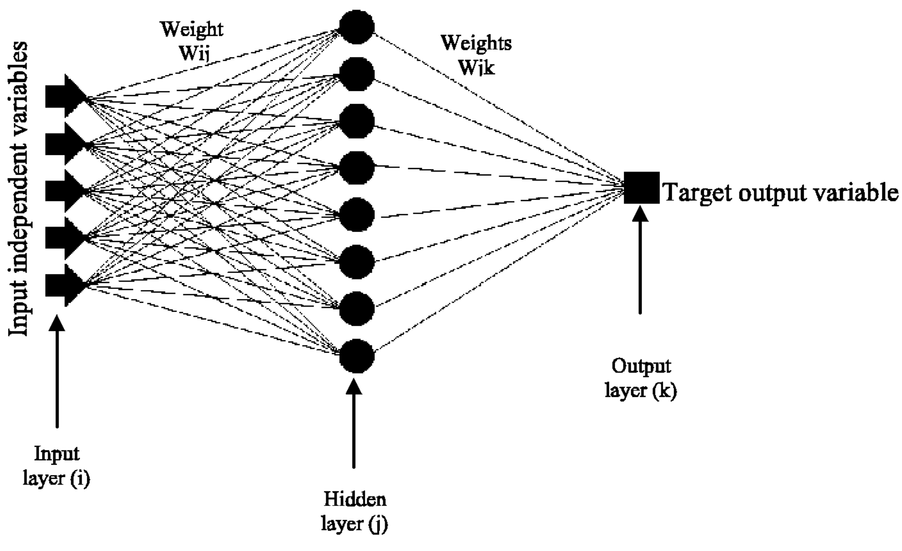

Figure 2. Schematic diagram of a three layer feed forward neural network

Each hidden node (j) receives signals from every input node (i) which carries standardized values $(\overline{Xi})$ of an input variable where various input variables have different measurement units and span different ranges. $\overline{Xi}$ is expressed as:

$$\overline{Xi} = \frac{Xi - X\min(i)}{X\max(i) - X\min(i)} \quad (3)$$

Each signal comes via a connection that has a weight(W_{ij}). The net integral incoming signals to a receiving hidden node (Net_j) is the weighted sum of the entering signals; $(\overline{Xi})$ and the corresponding weights; W_{ij}, plus a constant reflecting the node threshold value (TH_j):

$$Net_j = \sum_{i=1}^{n} \overline{Xi} W_{ij} + TH_j \quad (4)$$

The net incoming signals of a hidden node (Net_j) is transformed to an input (O_j) from the hidden node by using a non-linear transfer function (f) of sigmoid type, given by the following equation form:

$$Oj = f(Net_j) = \frac{1}{1+e^{-Net_j}} \quad (5)$$

O_j passes as a signal to the output node (k).

The net entering signals of an output node (Net_k): $Net_k = \sum_{i=1}^{n} O_j W_{jk} + TH_k$. (6)

The net incoming signals of an output node (Net_k) is transformed using the sigmoid type function to a standardized or scaled output $(\overline{O}_k)$ that is: $\overline{O}_k = f(Net_k) = \frac{1}{1+e^{-Net_k}}$ (7)

Then, $\overline{O}_k$ is standardized to produce the target output:

$$O_k = \overline{O}_k (O\max(k) - O\min(k)) + O\min(k) \quad (8)$$

Riad *et al.* [7] explained that the sigmoid function should be continuous, differentiable and bounded from above and below in the range {0, 1}. The calculated error between the observed actual value and the predicted value of the dependent variable is back propagated through the network and the weights are adjusted. The cyclic process of feed forward and error back propagation are repeated until the verification error is minimal [4].

2.4 Calibration and verification of the model

In case that limited data sets are available, cross verification can be used as a stopping criteria to determine the optimal number of hidden layer nodes [24] whilst avoiding the risk of over training [25]. Cross verification is a technique used commonly in ANN models and has a significant impact on the division of data [26]. It aims to train the network using one set of data, and to check performance against a verification set not used in training. This examines the ability of the network to generalize properly by observing whether the verification error is reasonably low. The training will be stopped when the verification error starts to increase [2]. The database was divided into training, cross verification and testing. For the ANN models described in this paper, 50% of the available data was used for training, 25% was used for the verification and 25% to test the validity of network prediction [16].

2.5 Determination of the model inputs

ANN models have the ability to determine which inputs are critical. They are useful mainly for complex problems where the number of potential inputs is large and where a priori knowledge is not available to determine appropriate inputs [27]. In this steady, a sensitivity analysis can be carried out to identify the importance of the input variables. This indicates which variables are considered to be most useful to be retained by the ANN model. The ANN model removes the input variables with low sensitivity. The sensitivity is presented by the Ratio and Rank. The Ratio reports the relation between the Error and the Baseline Error (i.e. the error of the network if all variables are "available"). The Rank simply lists the variables in the order of their importance.

3. RESULTS AND DISCUSSION

3.1 Artificial Neural Networks (ANN)

In the Saf-Saf river basin, the water resources mobilization is driven by the rapid increase of population, cultivated agriculture land, industrials facilities and other various socioeconomic variables. This rapid increase has produced unprecedented demands on the limited available water resources and has complicated the patterns of water consumption.

The types of networks considered are: MLP with two back-propagation algorithms (Broyden Fletcher Goldfarb Shanno Quasi-Newton BFGS [18 - 21] and Scaled Conjugate Gradient SCG) and RBF. During the analysis, many networks were tested. The best optimal ANN model found is MLP (BFGS 107) with 16 hidden nodes (Fig. 3, 4) and a minimal error of 0.014325 compared with the other types of ANN networks (Tab. 1).

Table 1. RMS Error in various neural networks.

ANN	Architecture	RMSE
RBF	7-5-1	0.047840
MLP (CG 110)	7-14-1	0.015892
MLP (BFGS 107)	7-16-1	0.014325

Table 2. Regression statistical parameters for the target output (WRM).

	Training	Verification	Testing
Data Mean	1.665625	3.695714	1.494286
Data S.D	2.023736	3.487257	2.116490
RMS Error	0.000318	0.014325	0.004663
Correlation	0.997379	0.960188	0.970863

The model has very good performance in verification with regression ratio (S.D. ratio) of 0.244 and the RMSE for training, verification and testing are small and close which indicates that the data sub-sets are from the same population [28] (Tab. 2). In addition, the correlation coefficient is higher than 96% for training, verification and testing which shows an excellent agreement between the observed and predicted water resources mobilization (Fig. 5).

The model training error for the independent cases is shown in figure 6. It graphs the RMS error of the network against epochs during iterative training of the back propagation training algorithms. In addition, it plots separate lines for the RMS error on the training and verification sub-sets of the independent cases at the end of the last iterative training run. The graph indicates that the range of RMS error of independent cases for both training and verification is very small [28, 29]. The ANN sensitivity analysis of response variables in both training and verification phases (Tab. 3) indicates that the importation of water is the most important intervention followed by the efficiency in water irrigation

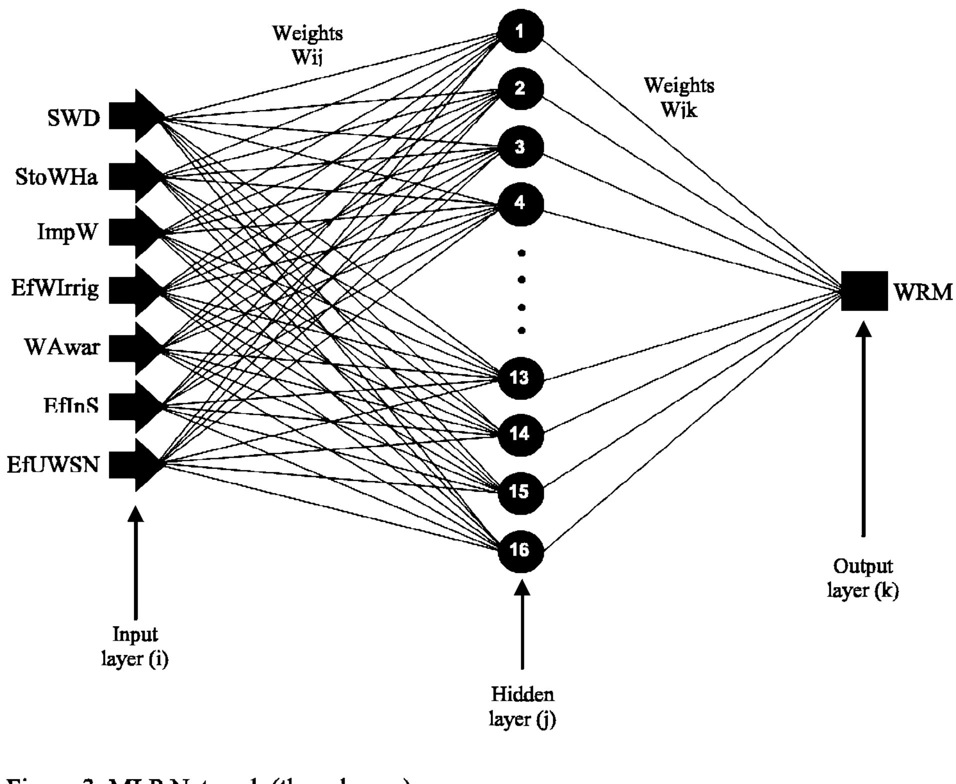

Figure 3. MLP Network (three layers)

The remaining policy interventions according to their order in the verification phase are: water awareness and education, efficiency in urban water supply network, efficiency of information system, storm water harvesting and sea water desalination. The results of the ANN model and expert opinion (Tab. 4) are similar only in ranking the first, the second and the fifth intervention which are importation of water, efficiency in water irrigation and sea water desalination whilst they differ in ranking the remaining variables.

Table 3. Sensitivity analysis of independent input variables

	StoWHa	ImpW	EfWIrrig	EfUWSN	EfInS	WAwar	SWD
Rank	4	1	5	2	3	7	6
Ratio	5.492940	123.2325	4.049400	12.13247	10.41647	2.454929	3.726960
Rank	6	1	2	4	5	3	7
Ratio	1.002058	9.983079	1.355602	1.108712	1.073650	1.285875	1.001495

Table 4. Ranking of input variables via expert opinion and judgment

	StoWHa	ImpW	EfWIrrig	EfUWSN	EfInS	WAwar	SWD
Rank	4	1	2	3	5	6	7

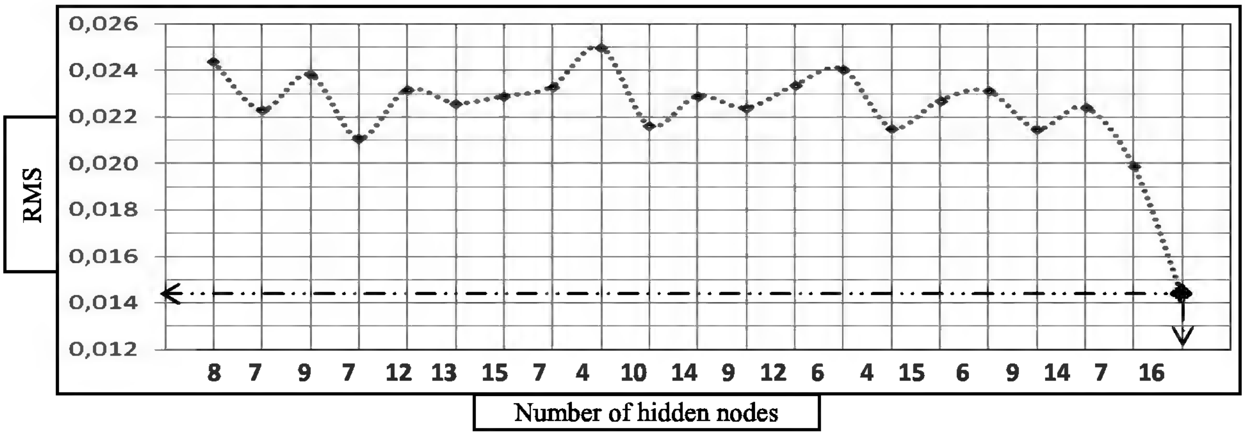

Figure 4. RMS Error versus number of hidden nodes

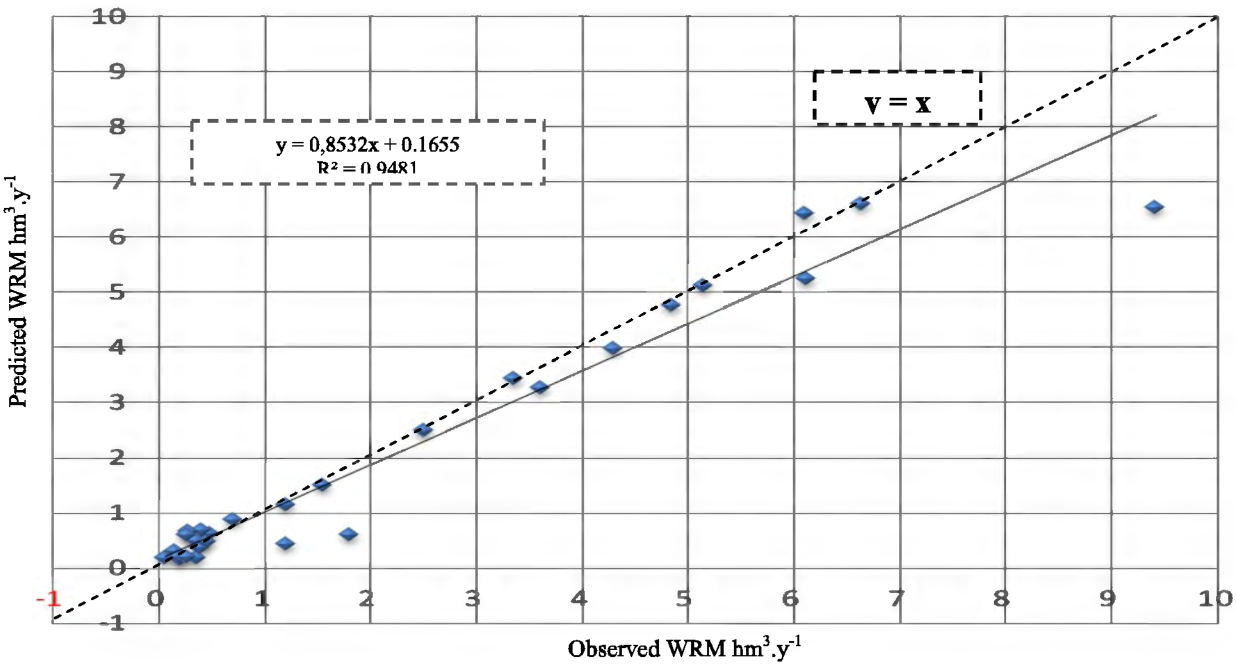

Figure 5. Predicted WRM versus Observed WRM $hm^3.y^{-1}$

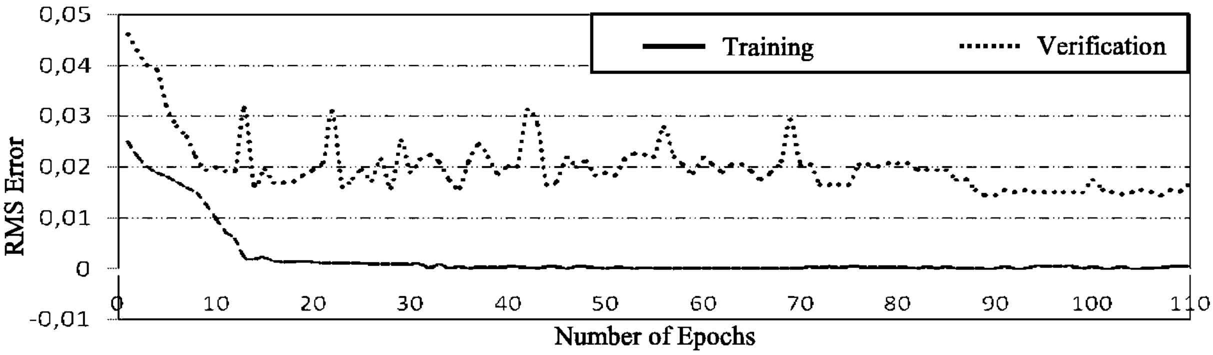

Figure 6. Training- Verification Error Graph for cases- response variables.

3.2 Principal Component Analysis (PCA)

The purpose of applying PCA module is to reduce the number of variables into a smaller number of dimensions (factors) and to classify variables and observations with similar characteristics with respect to these factors. There are 8 variables in the analysis, and thus the sum of all eigenvalues is equal to 8. The point where the continuous drop in eigenvalues levels off is at factor 3. Therefore, three factors were chosen for analysis with a cumulative variance of 73.30 %.

Table 5 presents variances of factors and their loadings from variables. The first factor corresponds to the largest eigenvalue (2.85) and accounts for approximately 35.692 % of the total variance. It is most correlated with the variables: importation of water, water awareness and education, and water resources mobilization (negative correlations).

The second factor corresponding to the second eigenvalue (1.548) accounts for 19.352 % of the total variance. It is uncorrelated with all variables (Tab. 6). The third factor corresponding to the eigenvalue 1.461 accounts for 18.262 %. It is significantly correlated with storm water harvesting and efficiency of information system (negative correlation).

Table 5. Eigenvalues of correlation matrix- response variables.

	Eigenvalue	**% Total variance**	**Cumulative Eigenvalue**	**Cumulative %**
1	2.855	35.692	2.855	35.69
2	1.548	19.352	4.403	55.04
3	1.461	18.262	5.864	73.30
4	0.963	12.043	6.827	85.35
5	0.576	7.205	7.404	92.55
6	0.349	4.368	7.754	96.92
7	0.183	2.290	7.937	99.21
8	0.062	0.785	8.000	100

Table 6. Factor-variable correlations, response variables (Underlined loadings are > 0.70)

	Factor 1	**Factor 2**	**Factor 3**
SWD	-0.301	0.519	0.222
StoWHa	0.102	-0.179	<u>-0.812</u>
ImpW	<u>-0.782</u>	0.560	-0.107
EfWIrrig	0.515	0.655	-0.278
WAwar	<u>-0.763</u>	-0.422	0.0434
EfInS	-0.371	-0.152	<u>-0.778</u>
EfUWSN	-0.686	-0.354	0.203
WRM	<u>-0.829</u>	0.418	-0.113

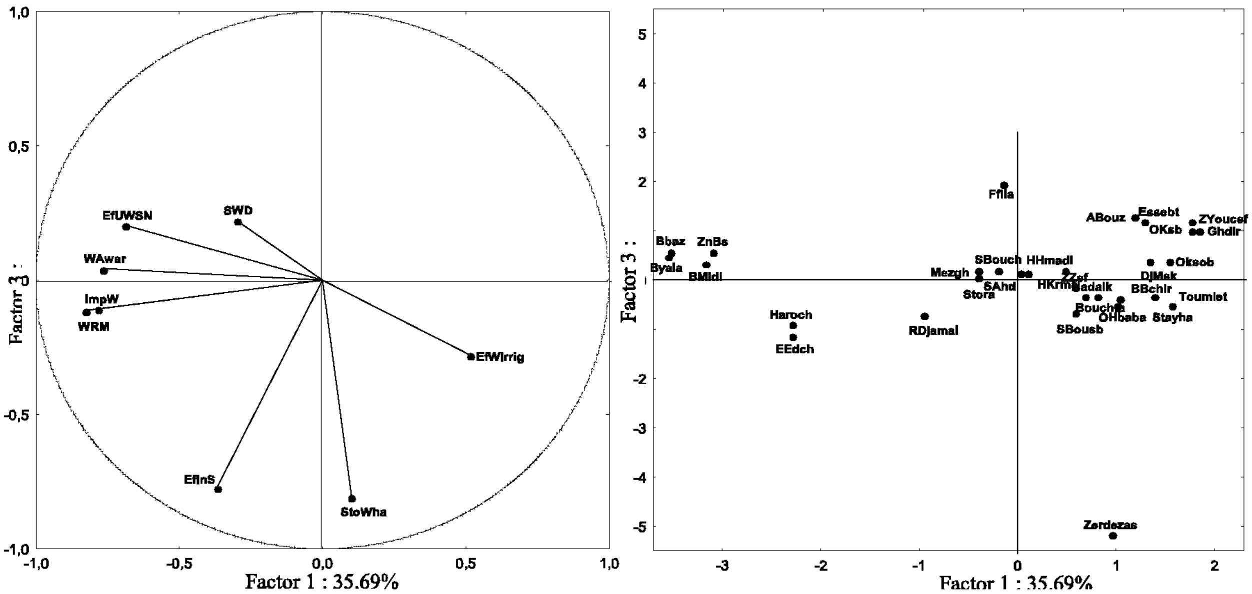

Figure 7. Projection of the variables and cases on the factor-plane (1x3) - response variables

Matching projection of the variables and cases on the factor-plane (1x3) shows that municipalities of Bouabaz, zone basse, Bouyala, Ben Mhidi (urban zones) are alike in terms of water resources mobilization, water awareness and education, importation of water and efficiency of urban water system network with low correlation. The municipalities of El Harrouch, Emjez Edchich and Ramadane Djamal are analogous in term of efficiency in information systems. Zerdezas is distinguished with storm water harvesting. The rural zones like zighoud youcef, El Ghdir, Essebt, Ain Bouziane, oued Ksob, Dj Mekcene, Stayha, toumiettes, Bouchtata and Ouled Hbaba can be versus urban zones, i.e. it is characterized by low importation of water, water resources mobilization, water awareness and education and bad urban water system network.

4. CONCLUSION

The obtained results indicate that MLP network proved to be the best ANN structure to model and predict the relationship between response variables and water resources mobilization in the Saf-Saf river basin. The water policy elements should be a combination of managerial and technical engineering interventions. Importation of water should have the top priority in the water policy as a potential strategic for socioeconomic demand, followed by efficiency in water irrigation. The urban municipalities located at the downstream of Saf-Saf river basin (Bouabaz, ben Mhidi, Zone Basse, Bouyala, Harouch, R.Djamal and E.Edchich) are characterized by very high WRM and their need for additional water resources including sea water desalination due to industrial, agriculture and population increasing demand. The rural municipalities located at the upstream of Saf-Saf river basin (Bouchtata, Beni-Bechir, S-Mezghich, El Ghdir, Es Sebt, Zerdezas, A-Bouziane, O-Hbaba, and Z-Youcef) are described with low WRM as results to their weak population and the absence of industrial activities.

The model also, strengthens the Integrated Water Resources Management (IWRM) approach through addressing that the variable of agriculture water consumption and population has the highest priority in WRM.

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Abbreviation

StoWHa: Storm water harvesting, $hm^{-3}.y^{-1}$

ImpW: Importation of water, $hm^{-3}.y^{-1}$

EfWIrrig: Efficiency in water irrigation, percentage

EfUWSN: Efficiency in urban water supply network, percentage

EfInS: Efficiency of information system, percentage

WAwar: Water awareness and education, number

SWD: Sea water desalination, $hm^{-3}.y^{-1}$

WRM: water resources mobilization, $hm^{-3}.y^{-1}$

RMSE: Root Mean Square Error