Daily irrigation water demand prediction using Adaptive Neuro-Fuzzy Inferences Systems (ANFIS)

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Abstract: - One of the main problems in the management of large water supply and distribution systems is the forecasting of daily demand in order to schedule pumping effort and minimize costs. This paper examines a methodology for consumer demand modeling and prediction in a real-time environment of an irrigation water distribution system. The approach is based on Adaptive Neuro-Fuzzy Inferences System (ANFIS) technique. The data was taken from a Cretan water company named O.A.DY.K and concerns the area of prefecture of Chania. ANFIS was comprised with traditional forecasting techniques as the autoregressive (AR) and autoregressive moving average (ARMA) models. ANFIS provide the better prediction results of daily water demand.

Key-Words: - ANFIS; forecasting; neuro-fuzzy; water forecasting, irrigation water, neuro-fuzzy forecasting

1 Introduction

In world level the consumption of water for various uses (domestic-urban, craft-based, industrial, and irrigator-rural) is increased with rapid rhythms. However, the offer has certain superior limits. In the most countries of world like Greece the daily demand of water is biggest (the summertime), when the offer (his availability) in the nature is minimal (in annual base). For this reason, the forecasting of consumption of water is important for any human requirement.

In Crete as in remainder islands the total aquatic resources that it used, emanates from the underground aquatic potential (carbonic water which is shaped by the White Mountains and sources), and only 3,5% emanates from surface waters. Hence, the daily prediction of water consumption is essential.

The main uses of water in the Chania are rural-irrigation, water supply and the tourism (recreation). The Prefecture Chania has today 150.000 permanent residents and 50.000 tourist and consequently the need of water supply is 150 m^3/resident X 200.000 = 30.000.000 m^3 annually. In addition, the extent has been cultivated are 572.805 acres which 251.098 acres are irrigated that is to say 44% percentage opposite 37% in the total in the country. The needs cover are 400 m^3/year X 500.000=200.000.000 m^3 annually while the current demand oscillates in the 100 millions of m^3 of water. Totally, the needs of next years to 2040 are appreciated 200 millions for irrigation and 60 millions for water supply of permanent residents and tourists=260 millions m^3 of water.

The models and techniques of water consumption used in forecasting are based on: a) Techniques which require a limited amount of data to produce future projections; they are used for long-term forecast. b) Techniques which require extensive data collection; the data is used to extract the statistical relationships; these methods are used for sort-term forecast.

As is well know, a plethora of prediction methods are proposed and used (see for example, Takagi-Sugeno Fuzzy System by Aqil et al. who are present an algorithm for real-time prediction of river stage dynamics of Cilalawi River in Indonesia [4]. Among them, the most widely used for water prediction purposes have a conceptual structure with different levels of physical information e.g. Random-effects model of Vagiona and Mylopoulos who are investigated water demand in the industrial sector [22]. This model include the price of water, the kind of products, the number of employees and dummies that declare if water is a basic input in the production process, if the cost of water contributes to the cost of production and the existence of water recycling methods.

The Open Prediction System by Kout et al. is a general predictive system applicable in a wide range of problem domains [10]. The special attention is paid to the tasks of prediction in multivariate time series motivated by problems common for utility companies that distribute and control the transport of their applicable commodity. Also, Categorical Approach by Tachibana is proposed [21]. In this research it analyzed and categorized hourly water consumption data gathered in a water purification plant in a metropolitan area in Japan for several year with so-called data-mining concept and tried to construct a precise prediction model trough the year.

In addition, there is a method which based on the conventional Wolf's algorithm for the largest Lyapunov exponent named Rough-Set method which generates prediction rules from observed data using statistical information by Chan et al. [6]. They present an application of a rough-set approach for automated discovery of rules from a set of data samples for daily water-demand predictions. The data covering information on seven environmental and sociological factors and their corresponding daily volume of distribution flow.

In recent year, artificial neural network (ANN) methods have been applied successfully to a number of multivariate forecasting problems in the field of water resources engineering. Maier and Dandy [13] proposed a method for forecasting salinity in the river Murray at Murray Bridge, in South Australia. Also fuzzy logic technique has been introduced by Halide and Ridd who are predicted local rainfall in January at Hasanuddin airport in Australia [7]. This station is close to the largest rice-producing area of Indonesia, Pinrang.

Also, Valenca and Ludermir present an Fuzzy Neural Network model for inflow forecast for the Sobradinho Hydroelectric power plant , part of the Chesf system [23]. The model is shown to provide better representation of the monthly average water inflow forecasting, than the model based on Box-Jenkins method, currently in use on the Brazilian Electrical Sector.

Lizaka et al. use an analyzable structured neural network (ASNN) who proposed a water flow forecasting method [11]. ASSN allows the dam operators to notice reasons of forecasting results and e4xtract knowledge about the forecasting from ASSN. There are also example where to approaches are combined to improve the forecasting performance as neural network and fuzzy system by Stüber and Germmar [20]. They are presented an approach for Data Analysis and Forecasting with Neuro Fuzzy Systems-demonstrated on flood events at river Mosel. Alvisi et al. compared methods of Fuzzy logic and artificial neural network approaches like [1]. The analysis is made with great attention to the reliability and accuracy of each mode, with references to the Reno river at Casalecchio di Reno (Bologna, Italy).

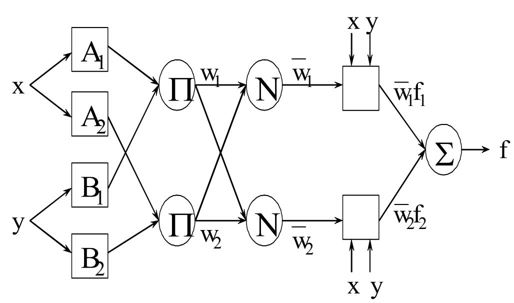
Recently, some researches have been applying adaptive network based fuzzy inference system (ANFIS) model for time series prediction [2], [9]. Atsalakis and Ucenic applied an ANFIS model to forecast the daily consume of water in area of Attika [3]. Also, Marcė R., et al. present a neuro –fuzzy modeling tool to estimate fluvial nutrient loads in watersheds under time-varying human impact [15].

Furthermore, data driven models such as hydrodynamic numerical (HN) model, a Muskingum-Cunge (MC) hydrological routing model, artificial neural network (ANN), and Adaptive Neuro Fuzzy System (ANFIS) have emerged as viable tools by Shrestha and Nestmann [19]. They are predicted river water level using physically based and data driven models. Liu et al. compare and analyze between time series Transfer Function Noise (TFN) of linear time series, the Grey system (GM) and an adaptive neural network fuzzy inferences system [12].

2 Methodology

Fuzzy inference systems (FIS) are one of the most famous applications of fuzzy logic and fuzzy sets theory [24]. The strength of FIS relies on their two-fold identity. On the one hand, they are able to handle linguistic concepts. On the other hand, they are universal approximators able to perform non-linear mappings between inputs and outputs [18]. Fuzzy rule based system incorporates the flexibility of human decision making by means of the use of fuzzy set theory. Fuzzy rules of the system make use of fuzzy linguistic terms described by membership functions [5], [17]. These functions are intended to represent a human expert's conception of the linguistic terms Fuzzy rules take the form IF (conditions) THEN (actions), where conditions and actions are linguistic labels applied to input and output variables respectively. In general, most of these specifications in codes and the functional requirements set by the users must be given in natural language to describe the expert's empirical knowledge of design modifications [16].

A network structure that implements fuzzy inferences system (FIS) and employs hybrid-learning rules to train is called ANFIS [8]. ANFIS has the ability to derive the expert's empirical knowledge, in form of rules, through the data using a learning algorithm. The hybrid learning algorithm proposed by Jang [8] combine the error back propagation and least square error method. The goal of ANFIS is to find a model that will correctly associate the inputs (initial values) with the target (predicted values). The ANFIS architecture is shown in Figure 1.



Layer 1 Layer 2 Layer 3 Layer 4 Layer 5

Fig. 1: ANFIS architecture by Jang [8]

A fuzzy inference system has two inputs x and y and one output z is assumed. The first-order Sugeno fuzzy model, a typical rule set with two fuzzy If-then rules can be expressed:

If x **is** A_1 **and** y **is** B_1 **then** $f_1 = p_1 \times x + q_1 \times y + r_1$

If x **is** A_2 **and** y **is** B_2 **then** $f_2 = p_2 \times x + q_2 \times y + r_2$

Nodes at the same layer have similar functions.

Layer 1: Every node i in this layer is an adaptive node with node function:

$$O_i^1(x) = \mu_{A_i}(x) \quad (1)$$

x(or y): is the input to the ith node A_i: is a linguistic label (such as "low" or "high") $O_i^1(x)$: is the membership grade of a fuzzy set A (= A_1, A_2) and it specifies the degree to which the given input x (or y) satisfies the quantifier A. As the values of these parameters change, the bell-shaped functions vary accordingly, thus exhibiting various forms of membership function on linguistic label $\mathbf{A_i}$. Parameters in this layer are referred to as premise parameters. The membership functions for A are described by generalized bell functions:

$$\mu_{A_i}(x) = \frac{1}{1 + \left[\left(\frac{x - c_i}{a_i}\right)^2\right]^{b_i}} \quad (2)$$

where a_i, b_i, c_i : is the parameter set. The membership function maps each element of x to a membership grade between 0 and 1.

Layer 2: This layer consists of the nodes labelled Π which multiply incoming signals and send the product out.

$$O_i^2 = \mu_{A_i}(x)\mu_{Bi}(y) \quad i=1,2 \quad (3)$$

Layer 3: The nodes labelled Π calculate the ratio of the i the rule's firing strength to the sum of all rules' firing strengths.

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2} \quad i=1,2 \quad (4)$$

The outputs of this layer are called normalized firing strength.

Layer 4: Every node i is a square node with a node function:

$$O_i^4(x) = \overline{w}_i \cdot f_i = \overline{w}_i(p_1 \cdot x + q_i \cdot y + r_i) \quad (5)$$

where $\overline{w}_i$ is the output of layer 3 and $\{p_i, q_i, r_i\}$ is the parameter set. Parameters in this layer will be referred to as consequent parameters.

Layer 5: This layer's single fixed node labelled Σ that computes the final output as the summation of all incoming signals.

$$O_i^5(x) = \sum_i \overline{w}_i \cdot f_i = \frac{\sum_i w_i \cdot f_i}{\sum_i w_i} \quad (6)$$

More information on ANFIS can be found in [8].

3 Results and discussion

The data concerns the irrigation water demand of prefecture of Chania in Crete. The daily data ranges from 1st of January 2002 until 31 December 2005, in total 1269 samples. The inputs data consist of daily time series data. The output variable consists of data one step ahead. The size of the training data includes 900 samples and 369 samples are used as evaluation data to exam the prediction performance of the model.

The number and the type of memberships function assigned to input variable was chosen with trial and error method and is set to two. After 100 epochs the model adapts the parameters of the membership functions. Figure 2 and 3 shows the form of the membership functions before and after the training process.

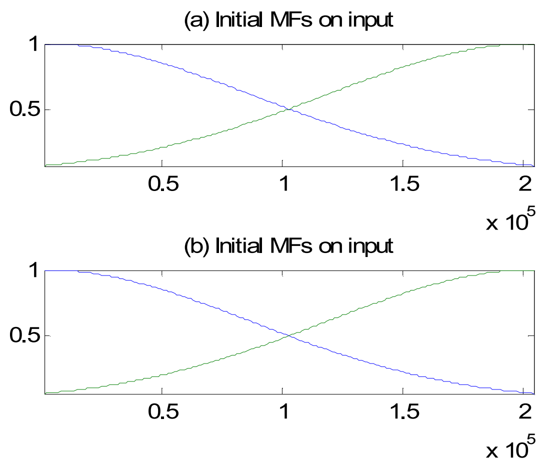


Fig. 2: Initial membership functions

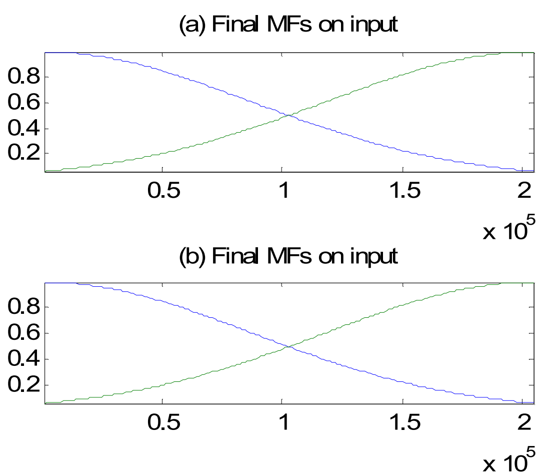


Fig. 3: Final membership functions

The follow rules and the corresponding linguistic variables are created by the anfis during the training phase:

If x **is** low **and** y **is** low **then** $f_1 = p_1 \times x + q_1 \times y + r_1$

If x **is** low **and** y **is** high **then** $f_2 = p_2 \times x + q_2 \times y + r_2$

If x **is** high **and** y **is** low **then** $f_3 = p_3 \times x + q_3 \times y + r_3$

If x **is** high **and** y **is** high **then** $f_4 = p_4 \times x + q_4 \times y + r_4$

A graphical representation of the rules and a sample of the fuzzy inference mechanism that take place on the fourth and fifth layer are depicted in Fig. 4.

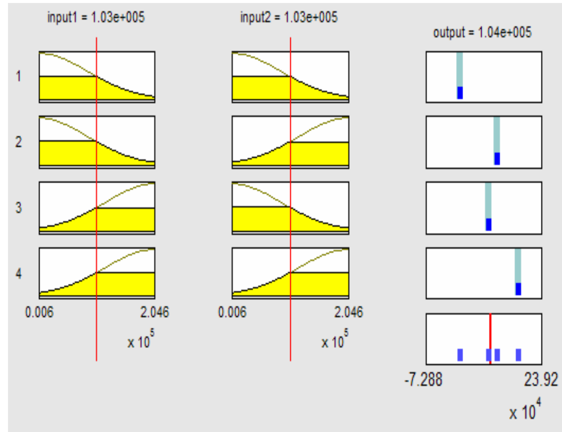


Fig. 4: A sample of depicting the fuzzy inference system mechanism

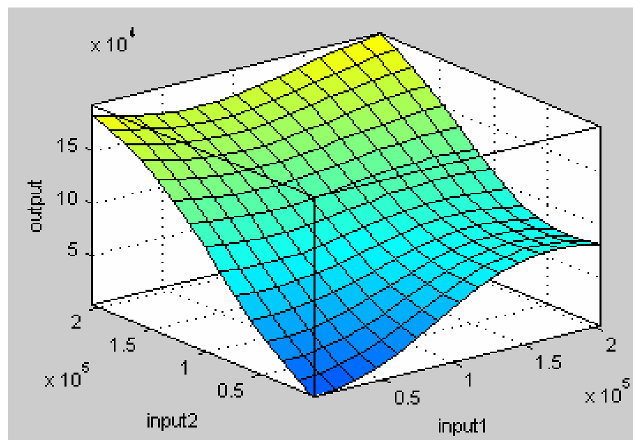


Fig. 5: ANFIS surface after training

Figure 5 presents the ANFIS surfaces that the training of the model has created. The absence of sharp ascent and descent declares that the training data distributed across the input space of the model in a somewhat uniform manner. Further this means that the model has captured the underling process dynamics.

After the completion of the training of the model, the evaluation phase takes place. The out of sample test is carried out and the output of the model (the forecasted irrigation water demand) is compared with the actual data (actual irrigation demand) of the next day. A graphical representation of ANFIS versus actual data is depicted in Figure 6 (concerns only a part of the evaluation data).

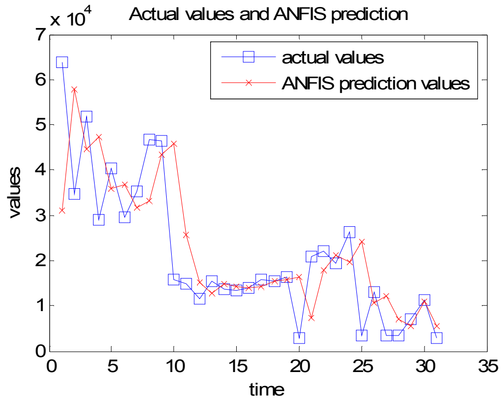


Fig. 6: ANFIS versus actual data out of sample prediction

As can been seen by the Figure 6 the two lines coincide in the most samples. Further comparison of the ANFIS model with the autoregressive (AR) and autoregressive moving average (ARMA) it takes place.

The performance of the models is examined using some main statistical measures that are well known in the international literature. The results of the mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE) are reported in the Table 1 foe AR, ARMA and ANFIS models.

Table 1: Error for the one step prediction

	AR	ARMA	ANFIS
MSE	1,9600	1,9306	1,8477
RMSE	1,4002	1,3802	1,3593
MAE	9,6932	9,6332	9,5803
MAPE	30,5633	30,124	33,7841

Clearly, there are many benefits of using ANFIS for prediction, including the following:
ANFIS has the smallest mean root square error, root mean square error and mean absolute error from AR and ARMA model. However, ANFIS has the biggest mean absolute prediction error.

4 Conclusion

This paper proposes a daily prediction of irrigation water demand using an adaptive neuro fuzzy inferences system (ANFIS). Eventually the ANFIS model got the steady performance considering AR and ARMA as verification. ANFIS model is simple to maintain and apply on forecast practically and has the follow advantages:

a. The ANFIS method allows interpreting the values of the parameters fitted. The transparent rule structure of ANFIS allows the extraction of information about the empirical relationship between inputs and output over time, drawing concise explanations. This a posteriori interpretation seems preferable to the a priori constriction of the data to an empirical relationship with an often dubious physical meaning. This open-box feature makes ANFIS an attractive exploratory data analysis tool, especially in situations were available models fail explaining observed phenomena.

b. ANFIS is a model-free, easy to implement approach. In contrast to time-series methods, little training is needed to calculate outputs with ANFIS. ANFIS implements a single-fitting procedure to nonlinear situations, without the need of establishing a formal model for the problem being resolved. Thus, no a priori information is needed about the empirical relationship between the explanatory and predicted variables, and the method suitability is always tested a posteriori.

c. With customary methods, variables frequently need transforming to enclose the problem into a linear relationship. Retransformation of results into real space is not straightforward and is dependent on the statistical properties of the constituent versus flow relationship. These properties do not always allow correct retransformation of variables leading to significant biases. Time-series methods require a constant time step during sampling. Anfis method avoids these drawbacks.

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