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FUZZY AND NEURO-FUZZY MODELS FOR SHORT-TERM WATER DEMAND FORECASTING IN TEHRAN*

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Abstract– Water demand forecasting cannot be described by any mathematical function because it is a complicated function of a large number of interacting variables. In this paper, several fuzzy and neuro-fuzzy models are presented and their results for short-term water demand forecasting in Tehran are compared. Weather data from three Tehran weather stations is weighted with the Thissen method and effective input data parameters are selected with regression of weighted effective weather and consumption data. The effective parameters include daily average temperature, relative humidity percent and last day, last week and last year water consumption. Consumption of all days between last day and the last week were also used. For the construction of fuzzy models a fuzzy rule-based approach is applied. The working rules are formulated from a set of past observations such as the relation between the parameters and the given input/output data sets. For neuro fuzzy modeling the toolbox function of Adaptive Neuro-Fuzzy Inference System (ANFIS) constructs a Sugeno Inference System (SFIS). The membership function parameters are adjusted using a back propagation algorithm in combination with a least squares method. Outputs of the fuzzy and the neuro fuzzy models demonstrate that the results of fuzzy models do not show high accuracy, but neuro fuzzy models produce better results. Besides, outputs of the neuro fuzzy models with just water consumption inputs have high accuracy. A comparison of outputs with the results of the Artificial Neural Networks (ANN) approach shows the capability of the ANFIS model to predict Tehran water consumption.

Keywords– Daily water demand, fuzzy sets, neuro-fuzzy inference system (ANFIS), temperature, relative humidity

1. INTRODUCTION

Water is used for many purposes such as drinking, irrigation and industrial consumption. In urban areas, water demand is a very important variable and is affected by several factors such as climatic conditions, population and city size, commercial and social conditions of people, cost of supply and characteristics of water distribution systems [1].

The future water consumption must be predicted because many properties of engineering applications and operational management of water distribution systems depend on this forecasting. In general, water demand forecasting is divided into three categories: long-term, median-term and short-term periods. Long-term period refers to water forecasting in future years that is used for the design of distribution systems. The median-term period refers to seasonal water consumption in a year, and short-term period refers to daily and hourly water demand. To manage water supply systems, the short-term water demand is very important and is used to determine the operational characteristics of the system such as pumps on/off,

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reservoir and treatment plan input/output, etc. Most of the previous research has focused on long-term water demand forecasting so there are few studies on short-term demand estimation.

Different methods have been applied for water demand prediction. Several researches in past decades have used regression models [2-5] and time series analysis [6-7]. More recently, some research can be found which use artificial neural networks (ANN) [8-9]. Application of fuzzy models has been limited to predict short-term power and electricity demand [10-11]; however, very few studies can be found on the application of intelligent systems for water demand prediction. Altunkaynak et al. [12] used the sugeno fuzzy method for predicting future monthly water consumption in Istanbul city. About 9 years of monthly water consumption in Istanbul city was used for training and testing the models. Tabesh et al. [13-14] and Karimi [15] used neural network and fuzzy systems for water demand forecasting of Tehran, respectively. In these studies the climatic parameters and daily water consumption used for modeling belonged to a short period of 3-4 years, and the effective parameters in the latter included daily average temperature, precipitation, number of sunshine hours and months. Deficiency of the data sets was the main disadvantage of these researches.

The city of Tehran (Capital of Iran) is one of the mega cities in the world with more than 8 million inhabitants at night and 12 million during the day. Tehran water demand has decreased from 5500 m^3/hd/yr to 1750 m^3/hd/yr during the last 45 years. This trend is also expected to continue more sharply to less than 1000 m^3/hd/yr in the next 15 years. According to United Nation criteria, Tehran will face a water crisis in the near future. About 70% of the required water is obtained from 3 reservoirs and the remaining 30% from a set of wells inside the city. No more surface water is available and most of the wells are at risk of contamination. Therefore, a robust water conservation program is required for optimum operation of the system and wise consumption of water. Thus, short term water demand forecasting is very crucial in this program.

The aim of this paper is to evaluate the potential of fuzzy and neuro-fuzzy models to predict future daily water demand in Tehran city. To do this, all the available water consumption and climatic data were gathered. More than 50 fuzzy and neuro fuzzy models are constructed and their results are evaluated. Sugeno fuzzy models are studied with three input parameters such as daily average temperature, relative humidity percent and last year consumption in this research. The fuzzy rule-based approach is applied for the construction of fuzzy models. To remove the weaknesses of fuzzy models that are not trained during the modeling, adaptive neuro-fuzzy inference system (ANFIS) with given input/output data sets is used for neuro-fuzzy models. In this model, membership function parameters are adjusted by a back propagation algorithm in combination with a least-squares method. Finally, the advantages of different fuzzy systems are studied and outputs are compared with the results of ANN models using the same data.

2. METHODOLOGY

a) Parameters selection

For this research, the only available information related to Tehran water demand were weather and water consumption data. To determine the effective parameters, a statistical analysis was performed. Weather data was prepared from the Islamic Republic of Iran Meteorological Organization (IRIMO), which included daily meteorological parameters from 1991-2003. This data was obtained from three stations in Tehran, Mehrabad, Tehran North and Doushan Tappeh. Water consumption data was prepared from Tehran Water and Wastewater Company, which included daily water supply from the first reported date (Spring 1991). The information from Tehran meteorological stations consisted of daily dry and wet bulb temperatures, maximum, minimum and average daily temperature, daily precipitation, sunshine period, wind speed, humidity, dew point and air pressure.

The meteorological data was coordinated with the consumption data from 1991. The weight of meteorological data was determined according to the relative area after data sorting of the three meteorological stations with the Thissen polygon method. Then, the weighted average of the parameters was determined. The relative areas covered by the Mehrabad, North and Doushan Tappeh were 46.7, 33.8 and 19.5 percent, respectively.

The following effective parameters were selected after a comprehensive investigation by regression between the meteorological parameters and water consumption:

- Daily average temperature, because of its high correlation with water consumption and possibility of future forecast by the meteorological organization with high accuracy.
- Relative humidity, which showed a high negative correlation.
- Last day to last week daily water consumption, because of high correlation.
- Last week and last year water consumption, because of high correlation and consideration of periodical (weekly and annual) impacts.

After determining effective parameters in modeling, two random and non-random approaches were applied for data selection. Data sets were divided into three parts: the first part included 60% of the data used for training the model. The second part consisted of 15% of data used for validation of the model. The third part included 25% of all data and was used for testing the model. In the non-random procedure the following categories of data were considered: from 1991 to 1998 (7 years) as training data, from 1998 to 2000 (2 years) as validation data and from 2000 to 2003 as testing data. In the random approach the data was selected randomly. Table 1 shows a sample of the organized data by both procedures.

In fuzzy models, the relations between meteorological parameters and water consumption were used to make fuzzy rules and the whole data were considered for testing because they do not use learning step for training fuzzy models.

Table 1. Random and non-random data organizing.

a) Random approach

No.	Day	Temperature (C)	Humidity (%)	Consumption (MCM)
13	Sat.	18	40	2.211
10	Wed.	23	30	2.307
6	Sat.	19	37	2.385
3	Wed.	17	34	2.279
11	Thu.	18	22	2.340
5	Fri.	17	43	2.335
14	Sun.	19	47	2.146
2	Tue.	16	35	2.278
12	Fri.	17	27	2.412
4	Thu.	19	40	2.264
1	Mon.	15	34	2.342
8	Mon.	21	42	2.325
9	Tue.	21	49	2.269
7	Sun.	19	33	2.264

b) Non-random approach

No.	Day	Temperature (C)	Humidity (%)	Consumption (MCM)
1	Mon.	15	34	2.342
2	Tue.	16	35	2.278
3	Wed.	17	34	2.279
4	Thu.	19	40	2.264
5	Fri.	17	43	2.335
6	Sat.	19	37	2.385
7	Sun.	19	33	2.264
8	Mon.	21	42	2.325
9	Tue.	21	49	2.269
10	Wed.	23	30	2.307
11	Thu.	18	22	2.340
12	Fri.	17	27	2.412
13	Sat.	18	40	2.211
14	Sun.	19	47	2.146

b) Model construction

i) Fuzzy approach

In this paper, at first, a fuzzy rule-based approach is applied for the construction of fuzzy models. The working rules are formulated from a set of past observations such as the relation between the parameters [16]. Singleton fuzzy system has been used for construction of the rules. A rule of a singleton fuzzy system has the following form:

R_i: if $u_1 = x_{i1}$ and $u_2 = x_{i2}$ and … $u_m = x_{im}$ then $y = s_i$, $i = 1{:}\ n$

where u is input, y is output, x is constant, s_i is the real value called the singleton of rule i and m is number of inputs.

To construct fuzzy models the fuzzy toolbox of MATLAB (FIS) is used. In the FIS, the toolbox grid partition approach is used for model construction and producing fuzzy rules. Two fuzzy models are constructed as follows:

F1) Inputs: daily average temperature and relative humidity with membership functions as shown in Figs. 1 and 2.

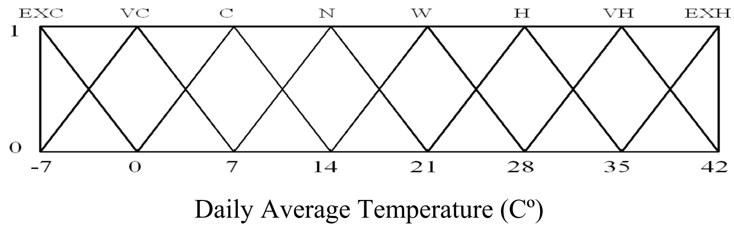

Fig. 1. Daily average temperature using triangular membership function

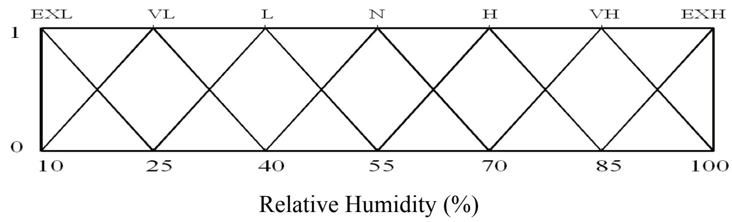

Fig. 2. Relative humidity using triangular membership function

Output: daily water consumption with singleton value such as Table 2.

Table 2. Water consumption values with singleton membership function (MF)

MF	S1	S2	S3	S4	S5	S6	S7	S8
Water Cons. (MCM)	1.36	1.48	1.60	1.72	1.84	1.96	2.08	2.20
MF	S9	S10	S11	S12	S13	S14	S15	
Water Cons. (MCM)	2.32	2.44	2.56	2.68	2.80	2.92	3.04	

F2) Inputs: daily average temperature and last year daily water consumption with membership functions presented in Fig. 1 and Table 2.

Output: daily consumption with membership functions like Table 2 but with 20 divisions.

Model F1 has 56 rules, all made from this general rule: "if daily average temperature is extremely high and relative humidity percent is extremely low, then daily consumption is extremely high". Model F2 has 120 rules, all made from this general rule: "if daily average temperature is extremely high and last year daily consumption is high, then daily consumption is extremely high". It should be noted that by using the last year water consumption, the trend component is considered automatically and effects of most of the parameters which may influence the water consumption (e.g. growth of population, standard of living, socio-economic aspects) can also be illustrated in the results.

ii) Neuro fuzzy approach

At the second step, neuro-fuzzy interface models were used for estimation of water demand. To do this, the neuro-fuzzy toolbox of MATLAB (ANFIS) is used. ANFIS is able to construct models with both subtractive clustering and grid partition categories. The topology of the ANFIS model with grid partition including 2 inputs which are divided into n and m sections, respectively, is shown in Fig. 3. Figure 4 represents an ANFIS topology with subtractive clustering including m input and n clusters.

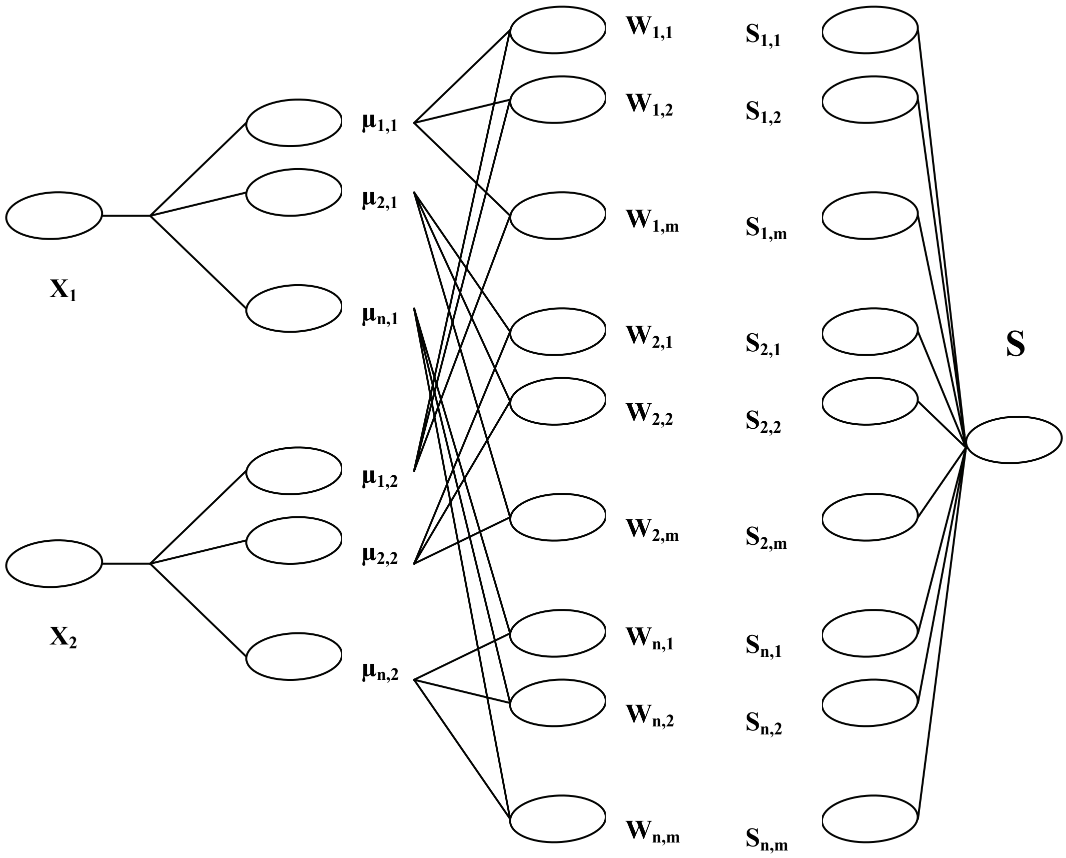

Fig. 3. Topology of fuzzy and neuro-fuzzy models with grid partition

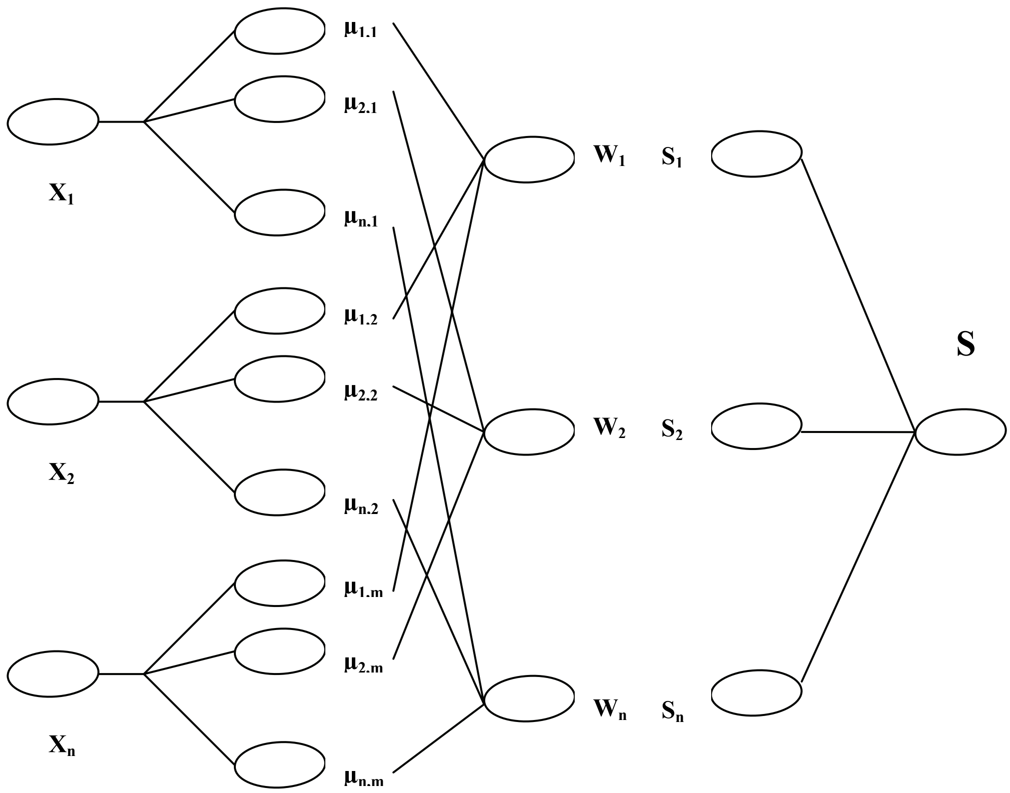

Fig. 4. Topology of neuro-fuzzy model with subtractive clustering

The model can be described as follows:

-Layer 1 (input layer): no computation is considered in this layer. Each node, which corresponds to one input variable, only transmits input values to the next layer directly. There are m input variables in this layer.

-Layer 2 (fuzzification layer): each node in this layer corresponds one linguistic label to one of the input variables in layer 2. In other words, the output link represents the membership value that specifies the degree to which an input value belongs to a fuzzy set. Input data is clustered using the subtractive clustering method. In the subtractive clustering category a bell-shaped Gaussian function is used for the membership function in the following form [17-19]:

$$\mu_{i,j}(X_j) = exp(-\frac{(X_j - c_{ij})^2}{2\sigma_{ij}^2}) \quad j = 1,2 \tag{1}$$

where, $\mu_{i,j}$ is the membership function or the degree of the membership of variable j in the i^{th} fuzzy implication rule, $\mu_{i,j}(X_j)$ indicates membership degree of the i^{th} input variable (X_j) and c_{ij} and σ_{ij} represent the center and the half width of the membership function for the j^{th} variable and the i^{th} fuzzy implication rule, respectively.

In the grid partition category triangular-shaped function is used for the membership function in the following form:

$$\mu(X) = \max\left(\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right) \tag{2}$$

where a and c locate the "feet" of the triangle and the parameter c locates the peak.

-Layer 3 (rule antecedent): a node represents the antecedent part of a rule. Normally a T-norm operator is used in this node. Output of the layer 3 represents the firing strength of the corresponding fuzzy rule.

-Layer 4 (combination and defuzzification layer): the single node computes the overall output as a summation of all the incoming signals. The output of N fuzzy implication rules is obtained as follows for grid partition and subtractive clustering:

$$S = \frac{\sum_{i=1}^{n}\sum_{j=1}^{m} S_{ij}W_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{m} W_{ij}} \qquad \text{Grid partition} \tag{3}$$

$$S = \frac{\sum_{i=1}^{n} S_i W_i}{\sum_{i=1}^{n} W_i} \qquad \text{Subtractive clustering} \tag{4}$$

in which w_i is the firing strength of the i^{th} fuzzy implication rule, n is the number of the clusters, S_i is the daily water demand estimation value from the i^{th} fuzzy implication rule and S is the estimated daily water demand.

Several neuro fuzzy models were constructed in which the output of all models was next day water consumption. The best models and their inputs are represented in Table 3.

Train and validation data are used for constructing neuro fuzzy models, while validation data controls the training error. Figure 5 shows the training and validation errors for neuro fuzzy models in 40 epochs.

Table 3. Classification of neuro fuzzy models for input data

Input Parameter	NF1	NF2	NF3	NF4	NF5	NF6	NF7	NF8	NF9	NF10	NF11
Average daily tem.	*	*		*			*	*			*
Relative hum. Per.	*				*		*	*			*
Last day cons.		*	*	*	*	*	*	*	*	*	*
Last 2 days cons.									*	*	*
Last 3 days cons.									*	*	*
Last 4 days cons.									*	*	*
Last 5 days cons.									*	*	*
Last 6 days cons.									*	*	*
Last week cons.			*	*	*	*	*	*	*	*	*
Last year cons.						*		*		*	*
Other parameters											*

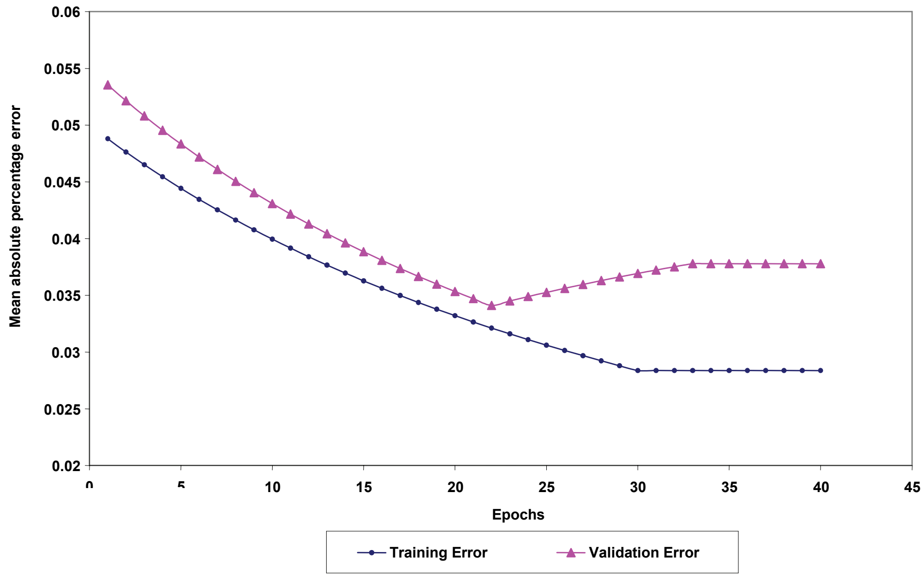

Fig. 5. Training and validation error in neuro fuzzy models

In this figure, minimum validation error indicates the optimum number of epochs for construction and testing of the model.

After constructing the fuzzy and neuro-fuzzy models, the following statistical indices are used for evaluation of the results:

i) Mean Square Error (MSE):

$$MSE = \frac{\sum_{i=1}^{n}\left(y_{actual,i} - y_{forecast,i}\right)^2}{n} \qquad (5)$$

where y_{actual} represents the actual daily water consumption, $y_{forecast}$ is the forecasted daily water consumption and n is data number. The unit of MSE is mcm^2.

ii) Normal Mean Square Error (NMSE):

$$NMSE = \frac{MSE}{\mathrm{var}(y_{actual,i})} \tag{6}$$

in which *var(y)* is the actual data variance.

iii) R^2:

R^2 coefficient is the second exponent of the correlation coefficient. If the estimated data is equal to the actual data, R^2 will be one. It is zero if there is no correlation between the forecasted and actual data.

iv) Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|y_{actual,i} - y_{forecast,i}\right|}{y_{actual,i}} * 100 \tag{7}$$

3. RESULTS AND DISCUSSION

a) Fuzzy approach

Results of the two fuzzy models are shown in Table 4 and Figs. 6 and 7. The advantages of models F1 and F2 are their simple structure and easy representation. The disadvantages of model F1, as shown in Fig. 6, are large error values and disability to evaluate the increase of water consumption with the passing of time. Model F2, as shown in Fig. 7, can evaluate the increase of water consumption with the passing of time clearly because of the inclusion of last year water consumption which enters the trend of consumption automatically; however, error values are still high.

Table 4. Results of the Fuzzy models

Type of data	Type of model	MSE	NMSE	R^2	MAPE (%)
Test data	F1	0.110	1.036	0.341	13.3
	F2	0.042	0.465	0.760	7.62
All data	F1	0.11	1.02	0.43	26
	F2	0.042	0.455	0.752	7.68

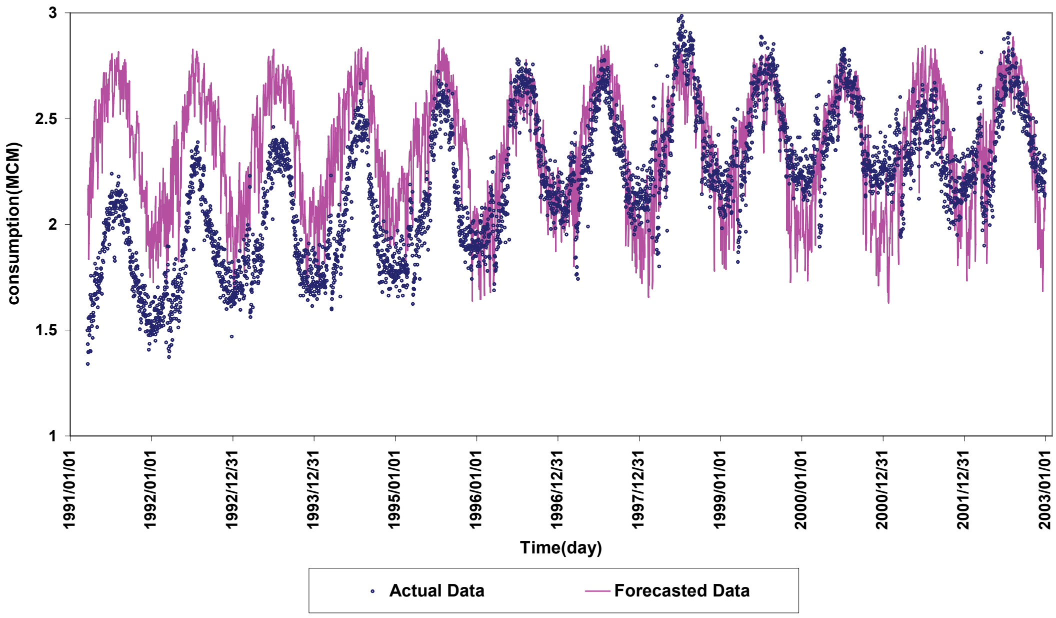

Fig. 6. Results of the model F1 (All Data)

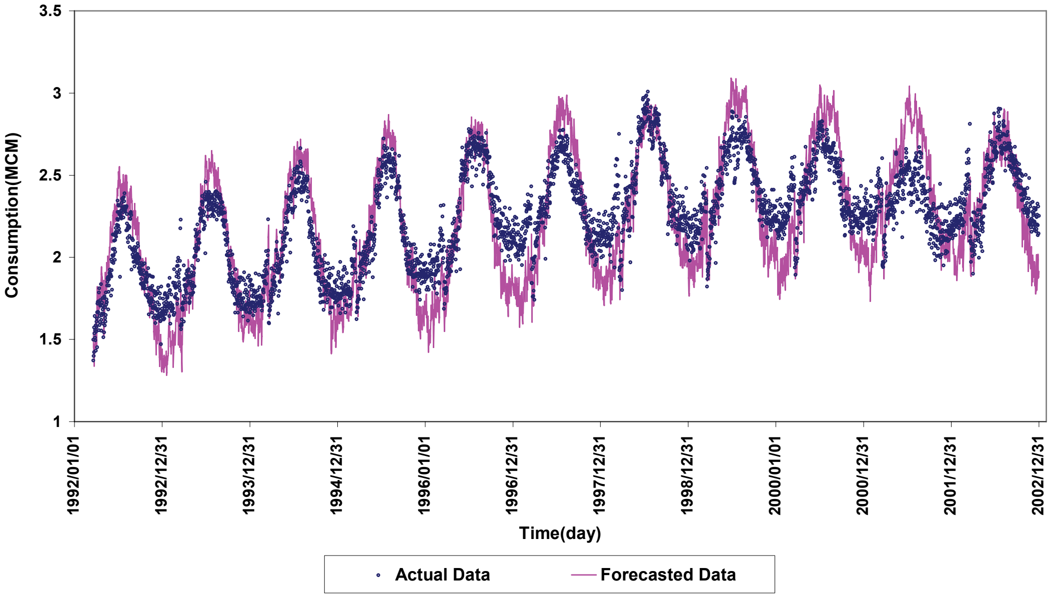

Fig. 7. Results of the model F2 (All Data)

b) Neuro fuzzy approach

The results of the neuro fuzzy models are represented in Table 5. Comparison of the results with both grid partition and subtractive clustering approaches and random and non-random procedures (Table 5) shows that the random data organizing procedure produces better results. One reason is that the effects of abnormal conditions such as drought periods can be incorporated in the random approach more realistically. For example, if some drought or wet periods occurred during the study time, the effects of these abnormal periods on seasonal water consumption are not included in just one of the train or test data. However they will be distributed randomly through the entire data set in all three stages of training, testing and verification. Therefore, the drought situation in Tehran, 2001 cannot affect the results of the models.

On the other hand, most of the models, including Neuro-fuzzy, ANN etc. are not good at extrapolation. It is apparent that water consumption has an increasing trend. The models are set up with the data at hand. In the future, consumption value will be greater than the current time and out of range of the training data. So, the models are forced to make extrapolation. In this study, the real reason that random selected data sets outperform non-random selected ones is the interpolation and extrapolation issues. When the non-random selected train data set is used, the model makes extrapolation and if train data is constituted randomly then the model will make a basic interpolation.

Figures 8-a and 8-b show that model NF1 with two inputs of average daily temperature and relative humidity percentage is not able to predict water demand properly. By applying random approach without considering previous consumption records this model cannot predict the seasonal and yearly trends of water consumption (Fig. 8a). On the other hand, this model with the non-random approach can predict the seasonal trend of water consumption (Fig. 8b); however, it does not show the increasing yearly trend of consumption during the study period and the error criteria are high (Table 5). It can be seen that error indices for NF1 are higher than F2 because in F2 water consumption is considered as the input parameter, having considerable effects on the results. Therefore, it can be concluded that, to obtain proper estimation of future water demand the inclusion of past records of water consumption is necessary.

Results of different neuro-fuzzy models with both grid partition and subtractive clustering approaches appear in Table 5 and show that, generally, both procedures produce the same results and the little existing difference could be because of the non-optimized nature of the grid partition approach. One of the main differences between the two procedures is that the subtractive clustering approach produces the best structure and needs less time to find the optimum structure. However, for the grid partition approach the best structure is identified by trial and error which is time consuming.

Table 5. Results of neuro fuzzy models for test data

Model	Input data procedure	Partition	MSE	NMSE	R^2	MAPE (%)
NF1	NR	SC	0.106	2.703	0.625	12.46
NF2	NR	SC	0.010	0.267	0.771	3.34
NF3	NR	SC	0.008	0.202	0.801	2.77
NF1	NR	GP	0.106	2.702	0.615	12.42
NF2	NR	GP	0.014	0.365	0.708	3.56
NF3	NR	GP	0.009	0.219	0.787	2.84
NF1	R	SC	0.056	0.529	0.471	9.76
NF2	R	SC	0.008	0.079	0.921	3.25
NF3	R	SC	0.007	0.066	0.934	2.96
NF1	R	GP	0.055	0.519	0.481	9.57
NF2	R	GP	0.008	0.079	0.921	3.25
NF3	R	GP	0.008	0.073	0.928	3.01
NF4	R	SC	0.007	0.065	0.935	2.93
NF4	R	GP	0.007	0.069	0.931	2.97
NF5	R	SC	0.007	0.066	0.934	2.91
NF5	R	GP	0.007	0.068	0.932	2.94
NF6	R	SC	0.007	0.074	0.926	2.85
NF6	R	GP	0.007	0.074	0.926	2.87
NF7	R	SC	0.007	0.064	0.936	2.92
NF7	R	GP	0.007	0.066	0.934	2.91
NF8	R	SC	0.007	0.072	0.928	2.82
NF8	R	GP	0.008	0.091	0.909	3.02
NF9	R	SC	0.007	0.064	0.936	2.86
NF10	R	SC	0.007	0.073	0.927	2.83
NF11	R	SC	0.008	0.086	0.915	3.00

Table 6. Results of neuro fuzzy models for test data (random and grid partition approaches)

Model	Input data procedure	Partition	MSE	NMSE	R^2	MAPE (%)
NF4	R	GP-2-2-2	0.007	0.067	0.933	2.97
NF4	R	GP-2-3-3	0.007	0.066	0.935	2.94
NF4	R	GP-3-3-3	0.007	0.064	0.936	2.90
NF4	R	GP-4-3-3	0.007	0.066	0.934	2.94
NF4	R	GP-5-3-3	0.007	0.065	0.934	2.95
NF4	R	GP-2-4-4	0.007	0.068	0.933	2.97
NF4	R	GP-3-4-4	0.007	0.068	0.932	2.94
NF4	R	GP-4-4-4	0.007	0.069	0.931	2.97
NF4	R	GP-5-4-4	0.007	0.068	0.932	2.94
NF4	R	GP-5-5-5	0.013	0.126	0.979	3.08
NF4	R	GP-6-6-6	0.010	0.091	0.910	3.20

To obtain the optimum structure of model NF4 the model input data are divided into different sections. This needs several models to be constructed. Some of them are presented in Table 6. The results show that the best structure is related to the grid partition of 3-3-3. It is also observed that with increasing the partitions, the model error indicators are higher. The reason may be the fact that with increasing the partitions, the number of required rules are increased exponentially, leading to complexity of the model.

For instance, the number of required rules for a model with partitions of 3-3-3 and 5-5-5 are equal to 27 and 125, respectively.

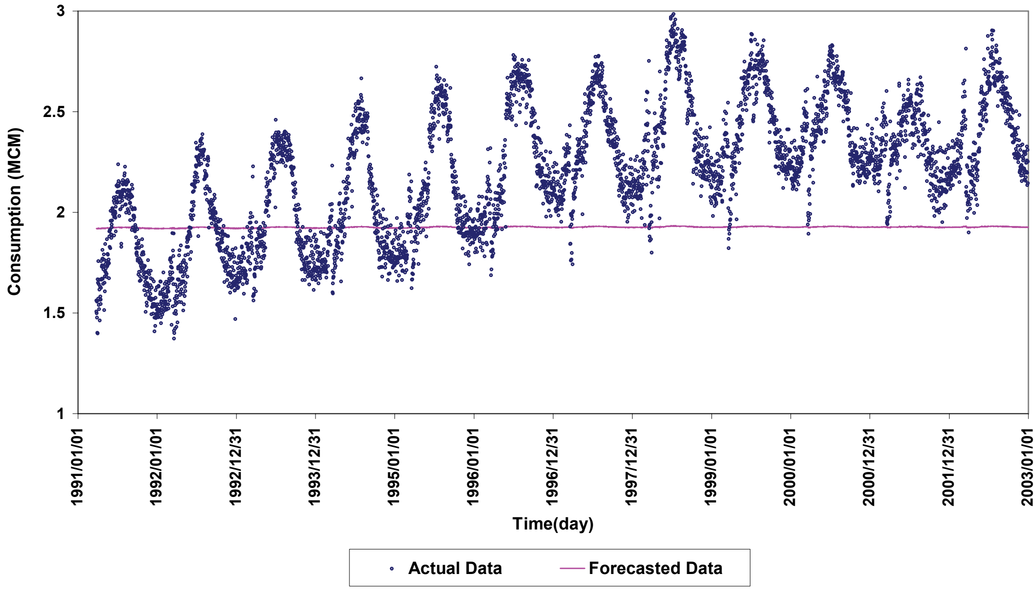

Fig. 8. a) Results of the model NF1 with random procedure (All Data)

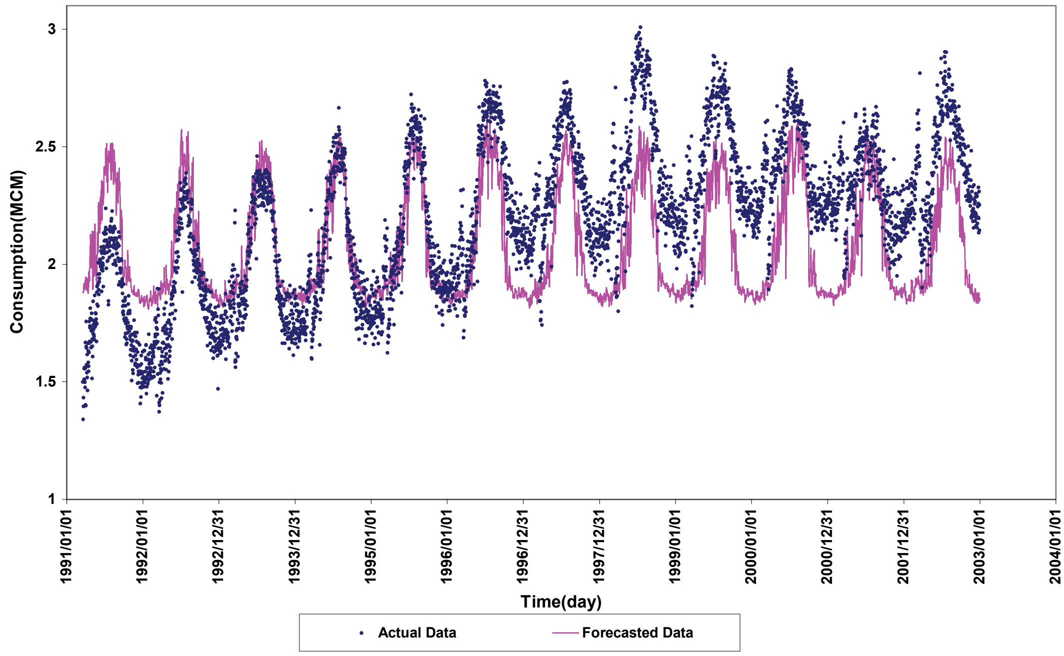

Fig. 8. b) Results of the model NF1 with non-random procedure (All Data)

Models NF2 to NF11 have good results and their statistical indices are close together for the random procedure. In all of these models, water consumption is considered as input data. Therefore, these models can evaluate trend and seasonal components very well. In Figs. 9 to 12, the results of the models NF3, NF6, NF9 and NF10 for test data are presented. Comparison of the outputs of these models producing the best results among more than 50 constructed models shows that models with meteorological parameters such as average daily temperature and average daily humidity have high errors and do not represent the trend and some seasonal components properly. Models with meteorological and water consumption parameters have much better results and can evaluate trend and seasonal components realistically. These models such as NF2, NF4, NF5, NF6 and NF7 have better results and can be used for forecasting water consumption. Models with only water consumption inputs such as last day and last week consumption or seven days during last week, and also last year water consumption have the best results, so they can be used for forecasting Tehran daily water consumption without needing to estimate any climatic input parameter. NMSE and R^2 indices are better in models with last day and last week consumption and MAPE index is better in models with last year daily water consumption than the other models.

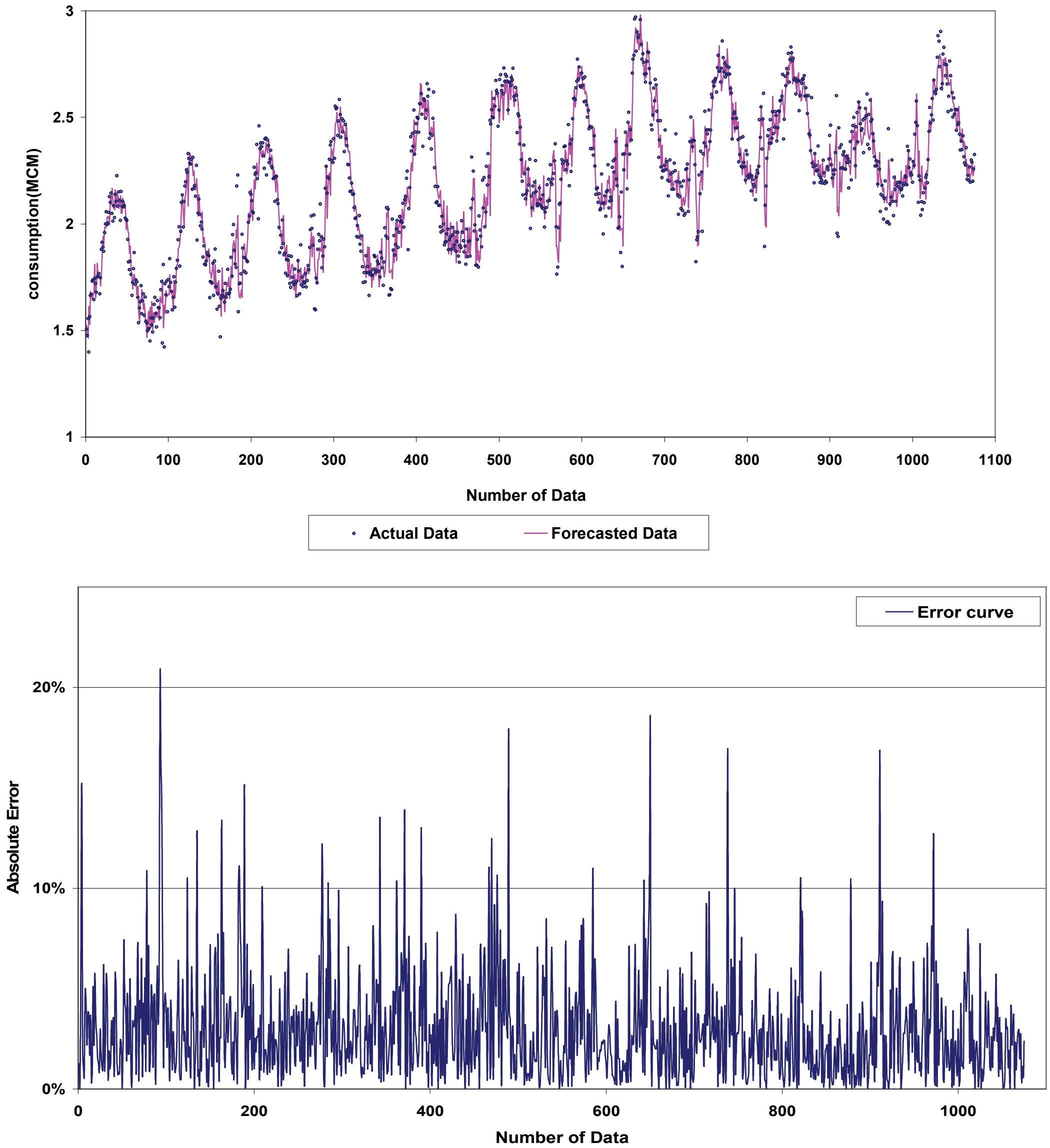

Fig. 9. Results of the model NF3 (test data)

Model NF3 is the same as model NF9. NF3 has two input parameters of last day and last week water consumption and NF9 has seven input parameters of last day to last week daily consumption. All of the statistical indices in model NF9 are better than the NF3, but the structure of the NF3 model is simpler and the training time is lower than the NF9. Model NF6 is the same as the model NF10. NF6 has three input parameters of last day, last week and last year daily consumption. NF10 has eight input parameters of daily consumption between last day to last week added to the three parameters of NF3. All of the statistical indices in model NF10 are better than the NF6. In general, models with more effective input parameters such as NF9 and NF10 produced better results than the models with low effective parameters such as NF3 and NF6.

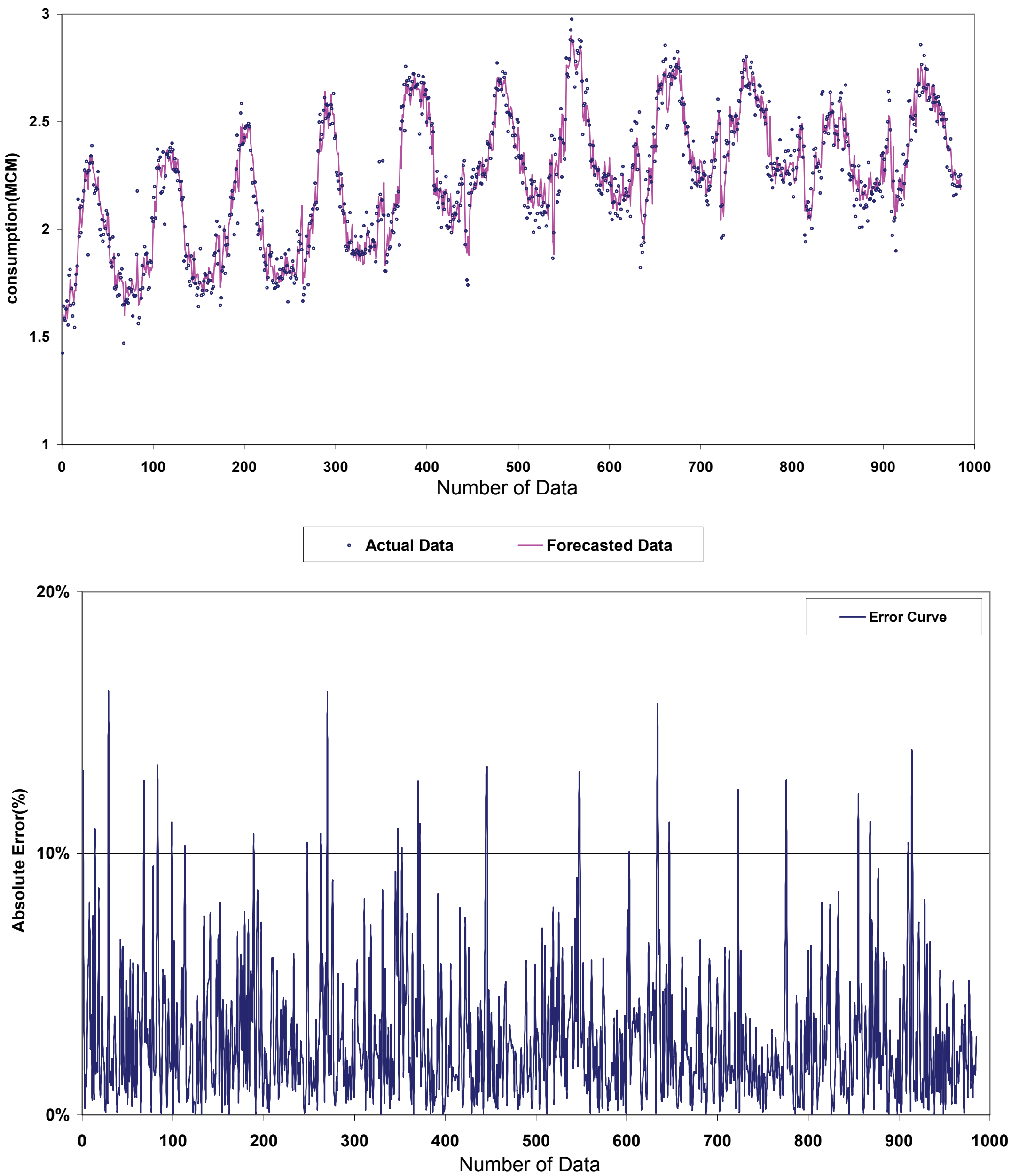

Fig. 10. Results of the model NF6 (test data)

Comparison between the results of models NF11 (with all input parameters) and NF8 (with five effective input parameters) indicates that selection of effective parameters in nonlinear models such as fuzzy and neuro fuzzy models are necessary, therefore all the statistical indices in NF8 are better than the NF11.

Evaluation of the results of different models showed that inclusion of last year water consumption as an input data leads to some changes in the outputs. By incorporation of this parameter some of the error indicators face higher values, however, two indices of MAPE and maximum absolute error show lower values. Results of models NF3, NF6, NF9 and NF10 are presented in Figs. 9-12, respectively. It is observed that for models NF3 and NF9 the maximum absolute error is 21% and 20%, respectively, however, for models NF6 and NF10 in which the last year consumption is considered, the maximum absolute error is about 17%.

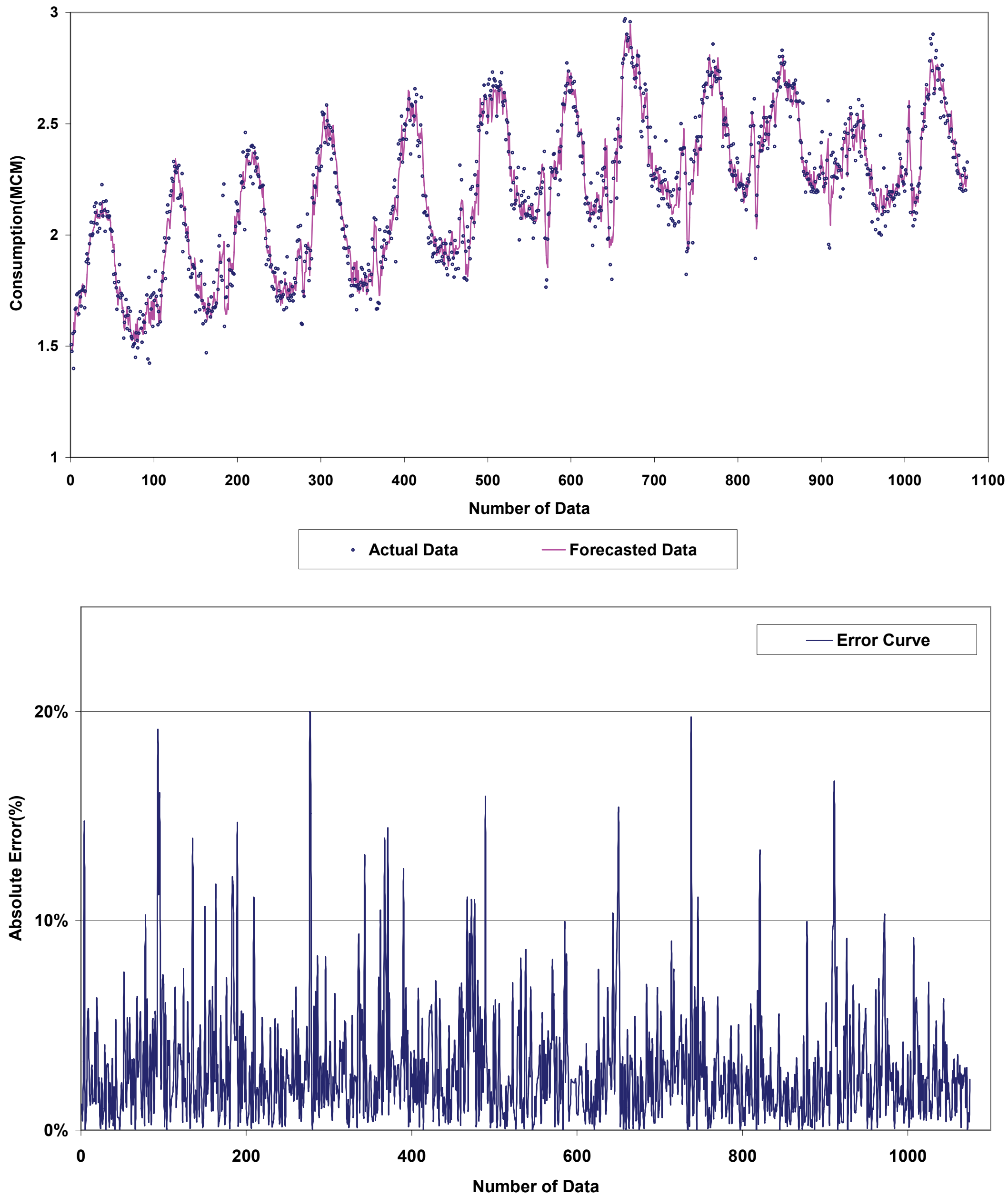

Fig. 11. Results of the model NF9 (test data)

To find the efficiency of the neuro-fuzzy method to predict the daily water consumption of Tehran, the results from some of the available research based on Artificial Neural Networks (ANN) are presented in Table 7. The Tabesh et al. [14] model includes data for a 4 year period from 1996 to 2000. The Tabesh [20] report includes three different ANN models (3 layers, 4 layers and RBF). His models are based on the climatic and water consumption data, the same as this research.

Comparison of ANFIS (models NF8, NF9 and NF10) and ANN results of Tabesh [20] show that MSE is the same for all models. MAPE and NMSE are lower and R^2 is higher for 3 and 4 layer ANN models, however, the RBF model produced higher errors. Generally, it is seen that the precision of the results of both methods are more or less the same. Therefore, it can be concluded that the neuro-fuzzy approach has a good potential to predict the daily water consumption of Tehran. The existing differences of results, especially with the Tabesh et al. [14] are because of differences between some of the data inputs and the total history time of the data.

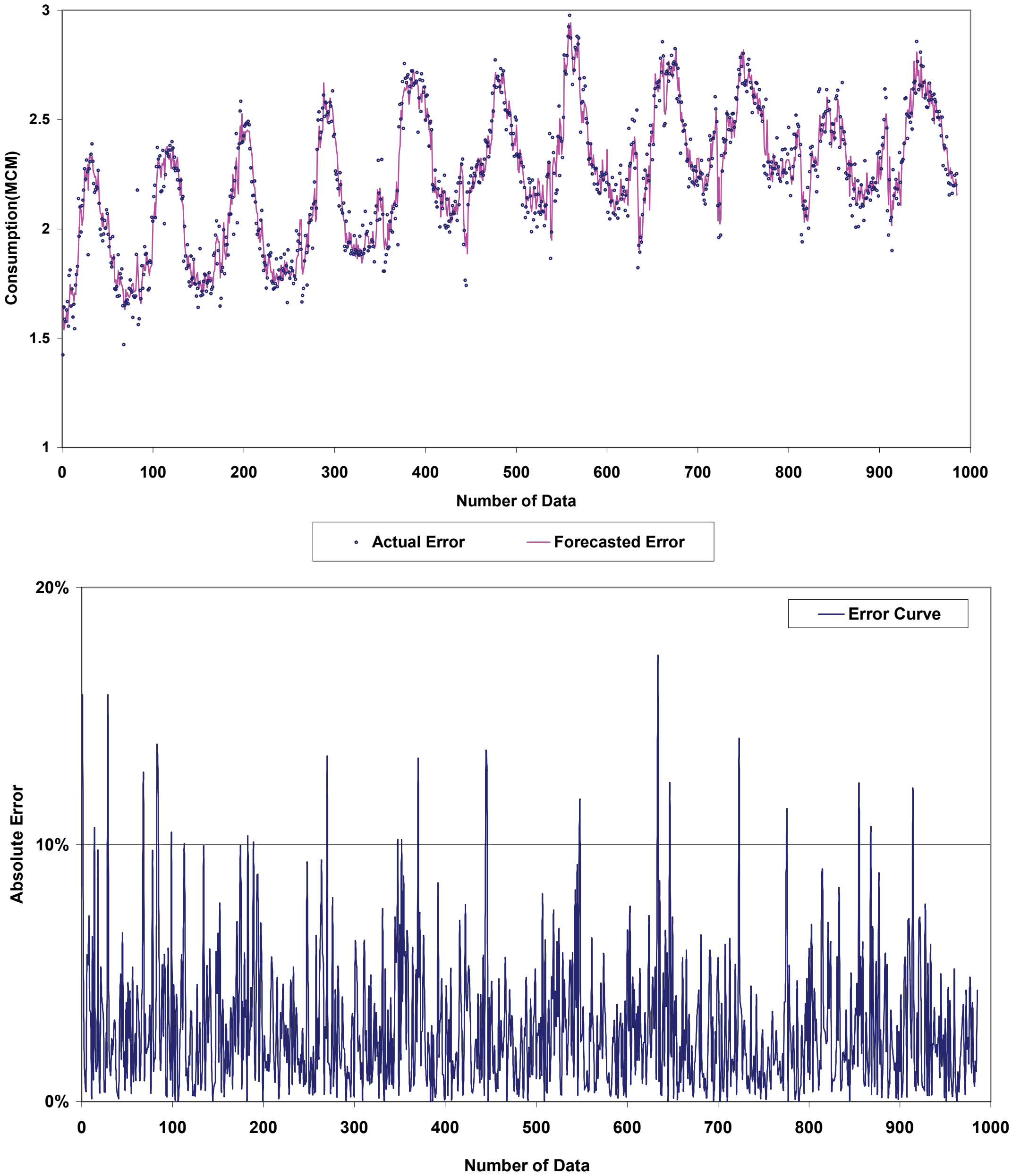

Fig. 12. Results of the model NF10 (test data)

Table 7. Results of some ANN models

Model	MSE	NMSE	R^2	MAPE (%)
[14]	-	-	0.808	1.715
[20] (3 layers)	0.006	0.057	0.943	2.69
[20] (4 layers)	0.006	0.059	0.941	2.74
[20] (RBF)	0.007	0.068	0.932	2.94

4. CONCLUSION

In this paper, adaptive sugeno fuzzy and neuro-fuzzy inference system (ANFIS) were used for modeling Tehran water demand. The effective parameters of the model were: daily average temperature, relative humidity percentage, last day, last week and last year consumption. The advantages of fuzzy models are their simple structure and easy representation, but in general, these models do not produce good results for forecasting Tehran daily water consumption. Their error values are very high because they cannot learn from input data in the training stage.

Comparison of constructed models based on two random and non-random approaches showed that the random data input approach produces better results. Neuro fuzzy models with random input produce very good results in comparison with the fuzzy models because these models have a high capability to understand and learn the consumption pattern. In general, in fuzzy and neuro fuzzy models, if the water consumption values are not considered as input parameters, they cannot predict the trend component. In non-linear models such as neuro fuzzy models, the selection of effective parameters with evaluating the correlation coefficient between input and output parameters are necessary. Therefore, the results of models with effective input parameters are better than models with all input parameters.

In the neuro fuzzy models, the models which only accept water consumption data such as last day to last week and last year daily water consumption as their input have very good results, so these models are proposed for forecasting daily water consumption in Tehran city. Also, these models do not need to forecast the input parameters (temperature and humidity) for the same day that daily water consumption is forecasted. In general, the NF3, NF6, NF9 and NF10 models have the best structure for forecasting the daily water consumption in Tehran. It should be mentioned that all the models based on fuzzy or Neuro Fuzzy logic systems should be updated regularly with more recent data to produce realistic results. Furthermore, comparison of neuro-fuzzy models with the neural network model (ANN) showed that the accuracy of neuro fuzzy models is the same as the ANN models. This is because of using the training stage for both types of models.

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