A long-term prediction of domestic water demand using preprocessing in artificial neural network

Sadegh Behboudian, Massoud Tabesh, Maliheh Falahnezhad and Farrokh Alavian Ghavanini

ABSTRACT

Both planning and the design of water supply systems require accurate and reliable prediction of water demand. In this study, artificial neural network (ANN) was used to predict the long-term water demand to determine the relationship between dependent and independent parameters. Using the stationary chain to solve the interpolating characteristic of ANNs, the study presents a reliable approach for long-term forecasting of water demand. The purpose of this study is to provide a convenient and reliable method for long-term forecasting of urban water demand while reducing the prediction uncertainty. In order to evaluate the accuracy of the prediction, multilayer perceptron (MLP) outputs were compared with results from the linear regression model. Findings indicate that MLP is an appropriate solution for monthly long-term water demand forecasting. Furthermore, it can reduce uncertainties and significantly increase the accuracy of the long-term forecasting.

Key words | artificial neural network, long-term forecasting, preprocessing, water demand

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INTRODUCTION

Prediction is a significant topic in the water industry. One of the main applications of forecasting is the estimation of municipal water demand. Yet, achieving the anticipated prediction accuracy with regard to the forecasting trends is quite challenging.

Drought, population growth, and increases in per capita consumption will give rise to a nearly global water crisis. On the other hand, water is a non-renewable commodity and makes the problem more complicated. In this situation, efforts should be made to optimize water consumption and prevent possible conflicts and quarrels to dominate water resources in the future. Furthermore, uneven distribution, either in time or resources, high evaporation rate, contamination of water resources, shortage of accurate information, price discordance, and social problems are yet other reasons that necessitate an accurate plan in order to optimize the efficiency of water resources' usage. In this way, an estimation of future water demand can help decision-makers to take necessary measures according to the possible crises and limitations. Forecasting domestic water demand and understanding its influencing factors are among the important steps in water crisis control and management. The effective solution not only lies in supplying water, but also in adopting necessary policies and schemes based on consumption patterns, and considering factors on the demand side. For this purpose, different econometric techniques and variables are assessed and analyzed. Several different data sets have been utilized, ranging from individual household data to aggregate data, for example, cross-sectional data (Chicione & Ramammurthy 1986; Chen & Yang 2009), time-series data (Billings 1982; Babel *et al.* 2007), and the most common cross-sectional time series data (Renwick & Archibald 1998; Mylopoulos *et al.* 2009). The widely used variables in these studies include household income, size of household, density of households, gross domestic product, average or marginal price, temperature, and precipitation (Kostas & Chrysostomos 2006; Mazzini & Montini 2006; Chen & Yang 2009). Most demand models are regression-based. They typically use the form of $Q = f(P, Z)$, where P is the price variable

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and Z is a factor such as income, household characteristics, and weather (Arbues *et al.* 2003; Babel *et al.* 2007; Schleich & Hillenbrand 2009). In recent years, several studies have been made with focus on the use of artificial neural networks (ANNs) for short-term (hourly or daily) or medium-term prediction (Topalli *et al.* 2006; Azadeh *et al.* 2007; Msiza *et al.* 2007; Firat *et al.* 2010). Since neural networks are trained based on a range of primary data (inputs and outputs), they fail to properly predict the data outside the mentioned range (interpolation problem).

In most previous studies that have been made on neural network forecasting purposes, a dependent variable (water consumption) is taken into account as an independent variable (considering the time intervals). Using this procedure, the consumption value (predicted in previous stages) is used for determining the amount of future consumption. Therefore, the error is increased at each stage and consequently these models are unable to predict data more than a few time steps. In multivariate models, in which water consumption is presented as a time delay, delaying parameters have the greatest impact on prediction of water consumption due to the high correlation between dependent variable and intervals of the same variable which are used as an independent variable in the model. Therefore, effects of other variables in predicting future consumption of water cannot be assessed.

Problems in long-term forecasting of water consumption using neural networks in previous studies can be summarized as follows:

- Interpolating nature of neural networks.
- Increasing error in forecasting results due to using delaying values of dependent variable as independent variables.
- Neglecting the effects of other variables affecting water consumption due to the high correlation between future water demand and consumption values in previous intervals.

This study mainly intends to provide a convenient and reliable method for predicting long-term water demand of urban areas while increasing prediction range and decreasing uncertainty of results. This paper demonstrates that the ANN approach is a good course of action for predicting long-term monthly water demand. It also tries to solve the interpolation problem of neural networks in long-term predictions. To obtain the relationship between dependent and independent parameters (estimating demand function) and to forecast domestic water demand, an artificial neural network was used in such a way that one can forecast long-term water demand.

METHODS

Although ANN has been mainly used for short-term forecasting, it can be shown that it is an accurate method for long-term forecasting of monthly water consumption. In this regard, two points should be considered: first, increasing time scope in forecasting (long-term forecasting) and second, increasing reliability and accuracy of forecasting.

In this study, a regression model and the ANN model were used for modeling water demand. Predicted results with both models were compared with each other. For this purpose, after estimating demand function, variables affecting per capita water demand were predicted for the desired forecast range and were given to the demand function to obtain the predicted values for per capita water demand.

Regression model

There are several variables affecting water demand, such as climatic, socioeconomic, and cultural variables which should be incorporated in modeling water demand. The domestic water demand function can be estimated by different models (linear and nonlinear). In this approach, for selecting the best model, the following criteria should be considered:

- The model should be consistent with reality and in accordance with theoretical expectations.
- The model should be used for policy-making and controlling purposes.
- The model should be used for prediction and providence.
- Statistical data should be collected correctly.
- All assumptions are based on classic theories.
- The estimation method should be correct.
- Model coefficients should be statistically significant.

The model should meet the theoretical expectations; R^2 should be high, R^2 and *adjusted-*R^2 should be close to each

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other. The F-statistic and the Durbin–Watson statistic verifying the entire regression must be significant.

Neural network

The *feed forward back propagated MLP* (multilayer perceptron) network was selected as the default network type for most MLPs. It has multiple neuron layers with nonlinear transfer functions that allow the network to learn nonlinear and linear relationships between input and output vectors. Learning or training in MLPs is supervised by comparing the desired output to a particular input. Learning involves presenting the input vectors, one at a time, at the input layer and passing them through the hidden and output layers, where the final network output is generated. At this point, the network output is compared with the desired output and the difference, i.e., the error, is then calculated. If the absolute error is larger than an acceptable threshold, the error is back propagated through the network; this process adjusts weights between input and hidden layers and those between hidden and output layers using an appropriate learning method to minimize the error in repeated processing of inputs by the network. The error threshold, or acceptable limit for error, defines the accuracy of the model and depends on practical considerations.

In this paper, to show the effect of variables affecting the water demand, the water demand function is estimated using the neural network. To obtain the relationship between dependent and independent variables and in order to predict the water demand, the *feed forward back propagated MLP* was selected as the network type (Rumelhart *et al.* 1986).

Therefore, delaying variables which decrease the accuracy of forecasting were excluded from the estimation model, because they increase error in long-term forecasting.

In this model, the same variables as those of the regression model were used:

$$Perc = f(I, MP, PO, E, MT) \tag{1}$$

where *Perc* is per capita potable water in cubic meter, *I* is the real per capita income of consumers in Rials (30,000 Rials = 1 USD), *MP* is the real mean price for potable water, *CPI* (consumer price index) is the price index for commodities and consumer services, *E* is the total literate individuals, and *MT* denotes the average maximum temperature.

Evaluation indices

A model evaluation method is to assess its estimation performance. To this effect, various criteria to assess and evaluate the performance of a model in terms of data estimation are available. Among these, conventional criteria like correlation coefficient, the square root mean square error (*RMSE*), mean absolute error (*MAE*), and mean absolute percentage error (*MAPE*) can be mentioned:

$$RMSE = \sqrt{\frac{\sum_{m=1}^{n} (X_p - X_o)^2}{n}} \tag{2}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} \left|\frac{(X_p - X_o)}{X_o}\right| \tag{3}$$

$$MAE = \frac{\sum_{m=1}^{n} |X_p - X_o|}{n} \tag{4}$$

in which μ is data mean, σ is the standard deviation of data, and n is the number of total data; p and o indices represent simulated and observed data, respectively.

Preprocessing of data

One of the most significant issues in long-term prediction with ANNs is their interpolating characteristic. To unravel this problem, data should be processed. After training the neural network with input and output data for the period 1997–2008, it is necessary to predict input values (independent variables) for the upcoming 20 years (predicted values are presented in Table 1) and simulate the neural network model with them to obtain future water demand values. Bearing in mind that the independent variables change significantly over time (with respect to observed data) and the model is trained in the range of observed data, the model would be unable to interpret these values and then predict outputs corresponding to these independent variables.

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Table 1 | Summary of statistics

Variable	Number	Min	Max	Mean	Standard deviation	Unit
Demand per capita	142	2.84	4.89	3.82	0.50	m^3
Real price	142	1.62	4.80	0.69	2.74	Rials
Real income per house	142	6.044	12,808	9.247	1,827	Rials
Price index	142	35.60	195.80	91.23	43.20	–

To address this problem, input and output data from the training block are taken to the same scale as input data from the prediction period (2011–2031). In doing so, the concept of stationary chain in time series was used (Greene 2007). Time series are stationarized when parameters of mean, variance, and correlation coefficients remain constant over time. The time series is made of trend, seasonal, and irregular components. The most significant step in statistical modeling is the irregular part of time series. Predictions based on the irregular component increase accuracy of the modeling and also produce more uniform data scale. Therefore, removing certain terms from time series and making the data more stationary are essential for preparing the data series for modeling with ANNs. In order to achieve a stationary condition in time series, first, the trends existing in data should be removed. Second, taking logarithm of the variables is another method which makes variables more static and also can change the scale of the data. It also eliminates collinearity between variables. These removed terms must be added to the forecasted water demand. Differencing is also another method for making time series static. However, once the prediction is over, it is impossible to convert output values from the neural network to the same unit as the water demand, so this method was not used (in this case the output values are from differencing ones). This preprocessing must be done before the training step in order to prevent saturating the neurons and also to increase the accuracy of the network.

RESULTS

Study area

Neyshabour with a population of 205,972 is located in the center of Khorasan Razavi Province in northeastern Iran. The annual average temperature in Neyshabour is 14.2 °C. Average annual precipitation is about 233.47 mm. A large proportion of water demand in the Neyshabour plain is supplied from wells and ground water resources. A nearly 90-cm annual loss in the ground water level has been observed, which leads to increasing the water crisis in Neyshabour. The position of Neyshabour City is shown in Figure 1.

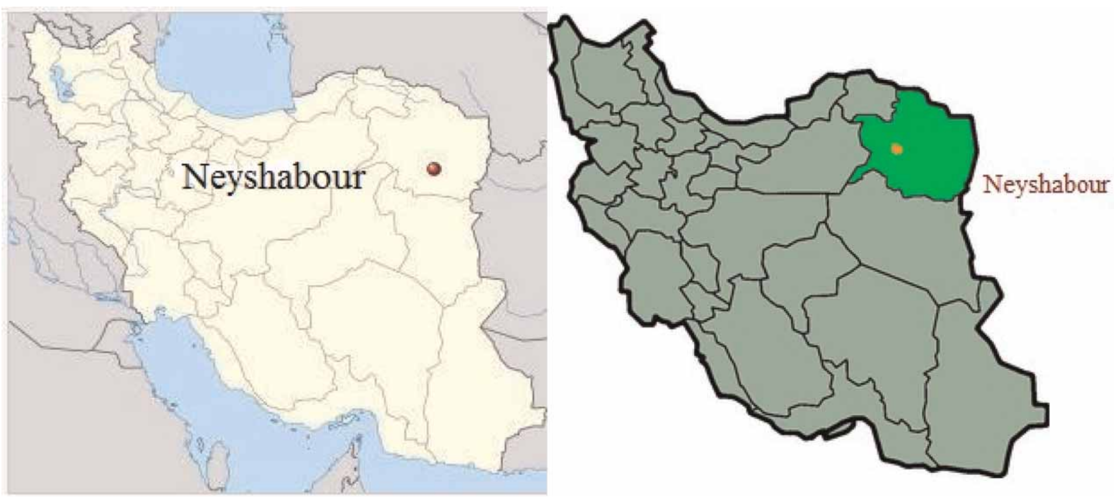

Figure 1 | Location of Khorasan Province and Neyshabour.

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Data

The utility bill data set used for the estimation was drawn from the water supply company in Neyshabour during 12 years from 1997 to 2008 and contained 144 monthly observations. Information about residential water consumption and its respective price were obtained from the operators of water utilities. Real water price is the price determined by water utilities, while actual water price is converted from the real water price when the price inflation is considered. The average price of water was calculated by dividing the total revenue from the Water and Wastewater Company in Neyshabour by the amount of water consumption in the same month. Monthly consumer price index, household expenditure, and the number of literate individuals were obtained from the Central Bank of Iran and household expenditure is a proxy for household income. The 12-year (1997–2008) monthly temperature data were obtained from a meteorological station inside Neyshabour. A summary of statistics for all variables is provided in Table 1.

Regression model

Since the Stone–Geary utility function – used for well-known essential goods – is the most adaptable utility function in this regard and has a high compatibility with facts and hypotheses of this research, it was used for extracting the water demand function.

Based on the Stone–Geary utility function, the long-term water demand function was estimated for 1997 to 2008 using time series data and economic evaluation of the ordinary least square method.

The final model, considering maximum mean temperature and total literates, was estimated as follows:

$$perc_t = \theta_0 + \theta_1\left(\frac{I_t}{MP_t}\right) + \theta_2\left(\frac{PO_t}{MP_t}\right) + \theta_3 E_t + \theta_4 MT_t + U_t \quad t = 1, \ldots, 120 \tag{5}$$

By substituting $PERI_t = \left(\frac{I_t}{MP_t}\right)$ $Pindex = \left(\frac{PO_t}{MP_t}\right)$ in Equation (5), for the following equation we have:

$$perc_t = \theta_0 + \theta_1\, Peri_t + \theta_2\, Pindex_t + \theta_3 E_t + \theta_4 MT_t + U_t \quad t = 1, \ldots, 120 \tag{6}$$

Model assumptions are:

$$\theta_0 > 0,\ 0 < \theta_1 < 1,\ \theta_2 < 0,\ \theta_3 > 0,\ \theta_4 > 0$$

Results of the demand function are shown in Table 2.

As the *t*-statistic indicates, all coefficients are significant at the confidence level of 95% and estimated coefficients are perfectly consistent with theory. The Durbin–Watson statistic shows that there is no correlation between the error terms. R^2 and F-statistic values are within the desirable level and the small difference between *adjusted*-R^2 and R^2 values indicates the absence of additional variables in the model.

Initial estimates of the demand function were subjected to auto-correlation of disrupting component. AR (1) (autoregressive (1)) and MA (1) (moving average (1)) were used to address this issue. The Dickey–Fuller unit-root test was performed on all variables and, considering the fact that the degree of all co-integrated variables is zero, there was no spurious regression.

In order to forecast water demand by the estimated model, independent variables should be predicted. Then, using these predicted values and the estimated model, future values for water demand can be predicted. According to Table 3, and under HADCM3 (A1B) scenario, the

Table 2 | Results of demand function

	Coefficients	Standard error	*t*-statistic	*p*-value
Constant	0.866	0.7444	1.16	0.246
PERI	0.000222	0.00003	6.02	0.0217
PINDEX	−0.00898	0.0038	−2.32	0.0051
E	0.00001	0.00	2.84	0.0030
MT	0.00931	0.00307	3.02	0.00
R^2	0.917	Durbin–Watson	1.7	
Adjusted R^2	0.913	F-statistic	248	

Table 3 | Forecast assumption variables

Number of literate individuals	Maximum mean temperature	Inflation index	Income (economic growth)	Water price
Pars Consult Co.	A1B	15%	5%	12%

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maximum temperature values of the LARS-WG downscaling model are predicted for the next 20 years. To this effect, the predicted values of population and total literates were used. The predicted values for per capita domestic income, CPI, and the average water price for 2011 to 2031 were 12, 5 and 15%, respectively.

Model accuracy

In order to assess the accuracy of the developed model, a comparison between observed and simulated data for the observation period (1997–2008) was conducted. Results depict that the accuracy of the estimated model is noticeable. Figure 2 depicts the comparison between actual water demand data and the calculated water demand by the estimated model. Additionally, two statistics for examining the forecasting accuracy, namely *RMSE* and *MSE*, were reported. The statistics suggest (the *RMSE* is 0.22 and the *MSE* is 0.13) that the model is fairly suitable for forecasting water demand in the future.

Obviously, for predicting per capita water demand in the future, using a neural network and a structural model, a series of dependent and independent variables were used.

Results obtained from data preprocessing

The feed forward back propagated MLP is the default network type for most MLPs. It has multiple layers of neurons with nonlinear transfer functions that allow the network to learn nonlinear and linear relationships between input and output vectors. For training the neural network, several training algorithms were used with different neurons (4–10 for each layer) and different number of layers (1–3 layers), and the Levenberg–Marquardt algorithm was selected as it produced the best result for the available data. The *MSE* performance function was selected since it is the default performance function for most networks. Three layers were implemented for the network by trial and error with respect to the best result (Exhaustive Search). The first layer contained nine neurons while the second one had ten neurons both with TANSIG transfer function. The third one had one neuron (since there was only one input) with the PURELIN transfer function.

The network weights were initialized with values equal to inputs. Input data were separated into three blocks: 70% were used for training, 15% for validation, and 15% for testing. If the validation error was increased six times sequentially, the training would be stopped. Training was

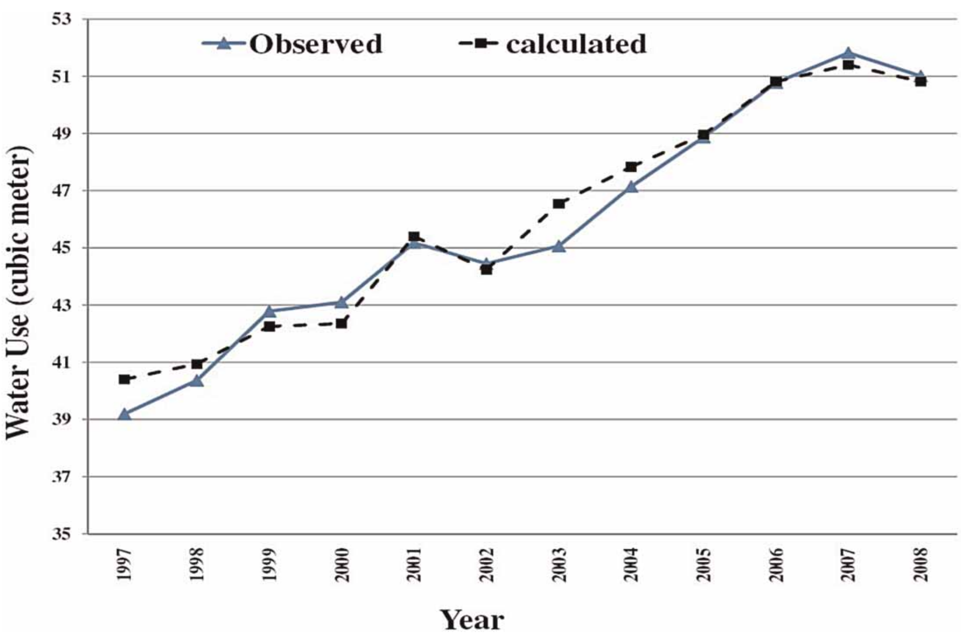

Figure 2 | Observed and calculated data.

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restarted using network weights which had been obtained from the previous run until we would reach acceptable results on the testing block.

First case

In this case, the trend component was removed from all data in observation and prediction stages. The trend component in the observation data for water demand was:

$$Y = 0.00703t + 3.32 \tag{7}$$

where t is time and Y is per capita demand. Removing the trend component improved the Dickey–Fuller test results.

According to the selection criteria, the best neural network model in this section was found. The gradient descent weight/bias learning and the resilient back propagation functions were used in the selected neural network with two middle layers of nine neurons each. According to Figure 3, in order to evaluate the model, output data from the test block were compared precisely with actual values.

According to the diagram, the model could forecast water demand rather well. Moreover, to assess the accuracy of the model, *MAPE*, *RMSE*, and *MSE* tests and the value of correlation coefficient were used. The values of these statistics are illustrated in Table 4.

These statistics indicate the good accuracy of the modeling. Therefore, the predicted values of independent variables were put in the simulated neural network as input data to obtain per capita water demand for the future.

Once the output values were predicted using the neural network, the data should be denormalized, and the previously removed trend of water demand values should be added to the values predicted by the neural network model. Comparing ANN predicted results with predicted values for per capita water demand obtained from the Stone–Geary function are shown in Figure 4. Based on preprocessing which was implemented on the input data, the model could follow the general trend in water demand up to the 170th month. It could also simulate the seasonal changes. As, after the 170th month, predicted input data were not in the range of data with which the network was

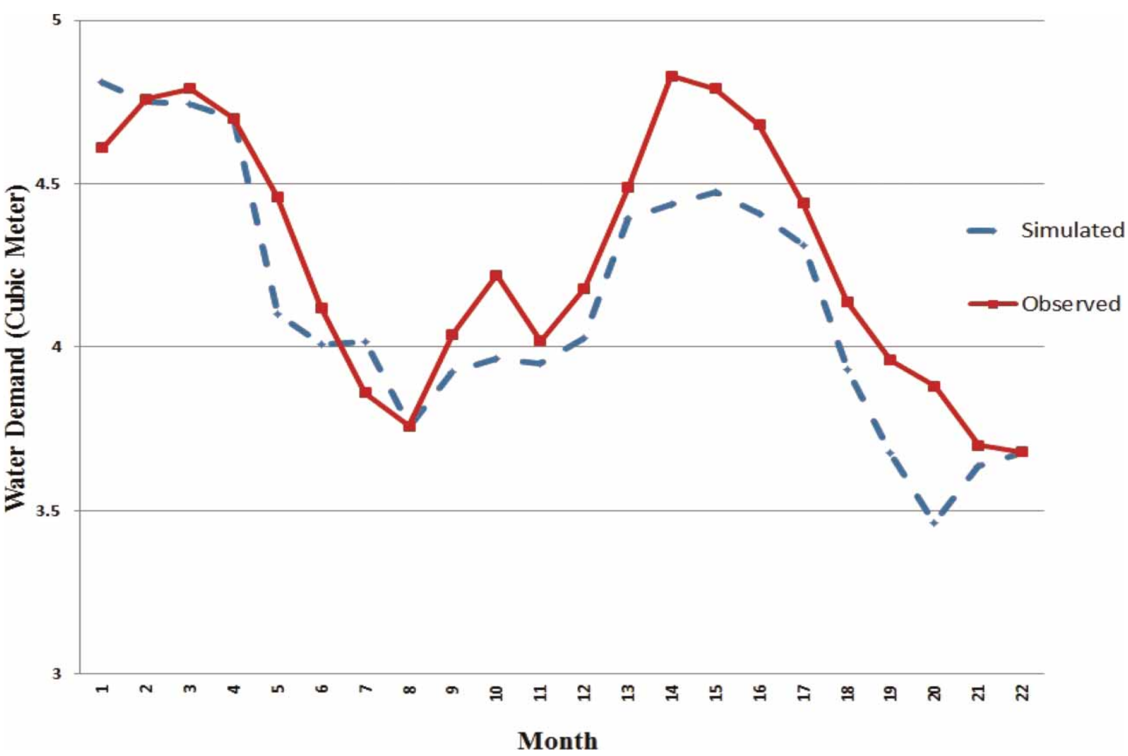

Figure 3 | The comparison between observed and predicted per capita water demand for the test period (22 months).

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Table 4 | The values for statistical parameters of variables

RMSE	MSE	MAPE	R
0.044	0.044	0.038	0.91

trained, it fails in properly modeling the changes; therefore, the model error increased with increasing values of independent variables which were increased with time as well. The difference between the water demand values predicted by each model in the first 170 months was caused by errors which were generated by modeling.

Second case

In order that the scale of input data values in prediction phase to be closer to data used in the training phase, logarithm was taken from data, and the existing trend in variables was removed. Taking logarithm makes the data series smoother. Likewise, it helps a time series to be more static and increases the modeling accuracy (Greene 2007). After removal of the trend from the time series, they were normalized (standardized) for modeling. The Dickey–Fuller test results showed that taking logarithm improves test values.

The best neural network model in this section was found based on the selection criteria. The gradient descent with momentum weight/bias learning and one step secant back propagation functions were used in the selected neural network with the structure of two middle layers with seven neurons in the first layer and eight neurons in the second layer. Figure 5 shows the accuracy comparison of the model in the test area with actual values.

Figure 6 shows the error surface in 3D and the number of neurons in the first and second layers. In Figure 7, the 3D surface of the correlation coefficient value and the number of neurons in the first and second layers clearly show that the neural network in the third case (with configuration of 5:7:8:1) has a greater value of R and a lower error.

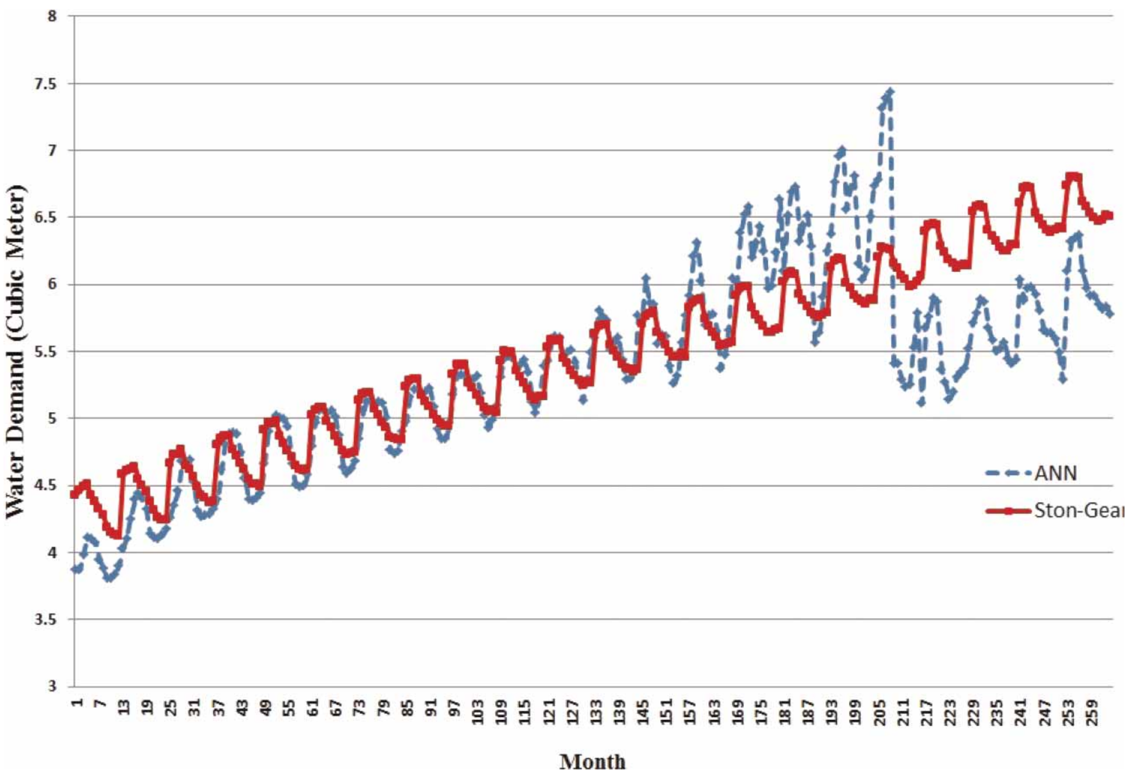

Figure 4 | The comparison between predicted per capita water demand by Stone–Geary model and ANN for the period 2011–2031.

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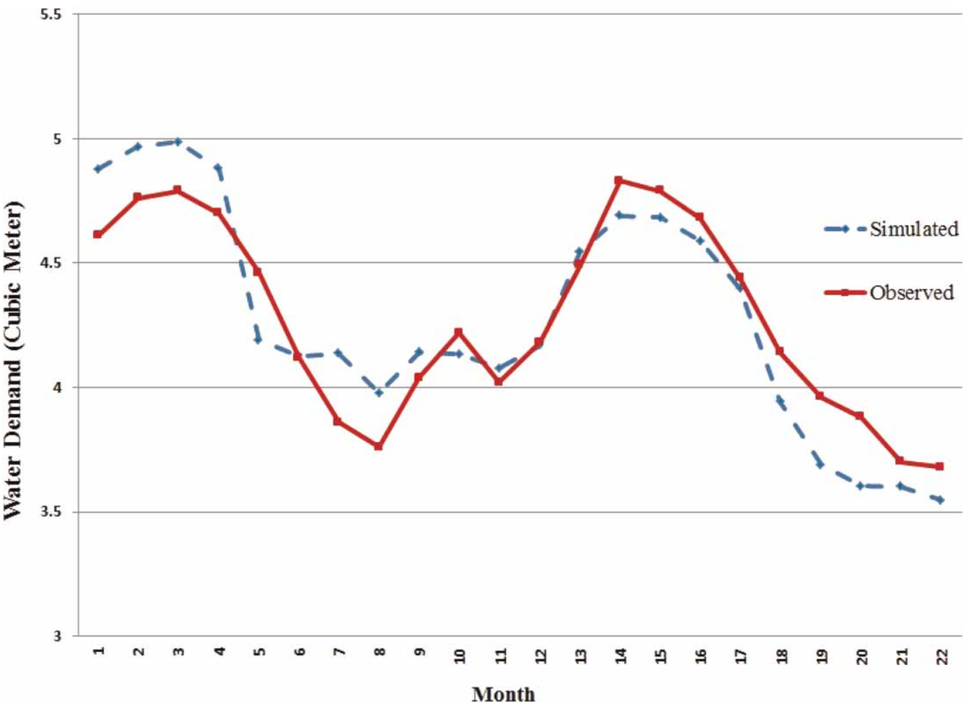

Figure 5 | The comparison between observed and predicted per capita water demand for the test period (22 months).

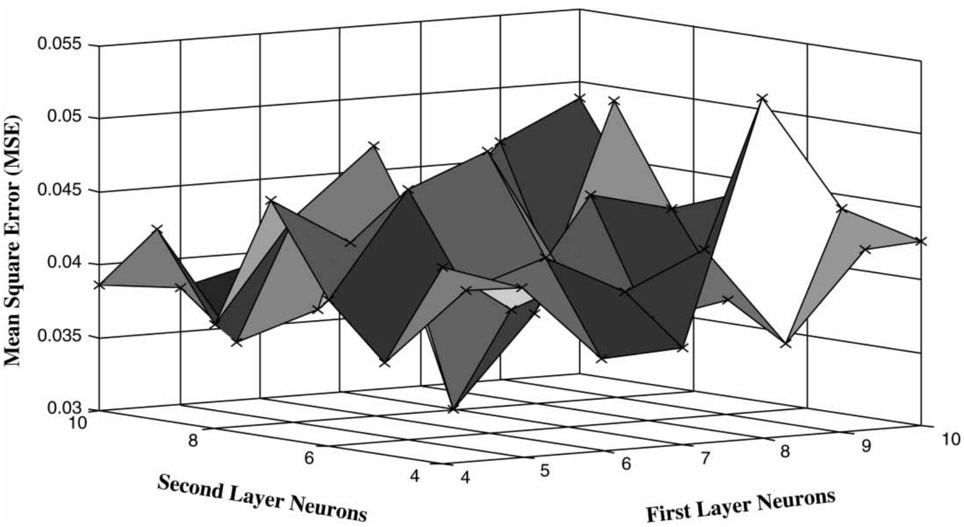

Figure 6 | The error value in 3D graph according to total of neurons on first and second layer.

Furthermore, to assess the accuracy of the model, *MAPE*, *RMSE*, and *MSE* tests were used along with the correlation coefficient value. These statistical values are shown in Table 5.

These statistical values indicate that the accuracy of modeling is acceptable. Therefore, this simulated ANN can be used for predicting water demand. After obtaining the output values by the neural network, the data must be

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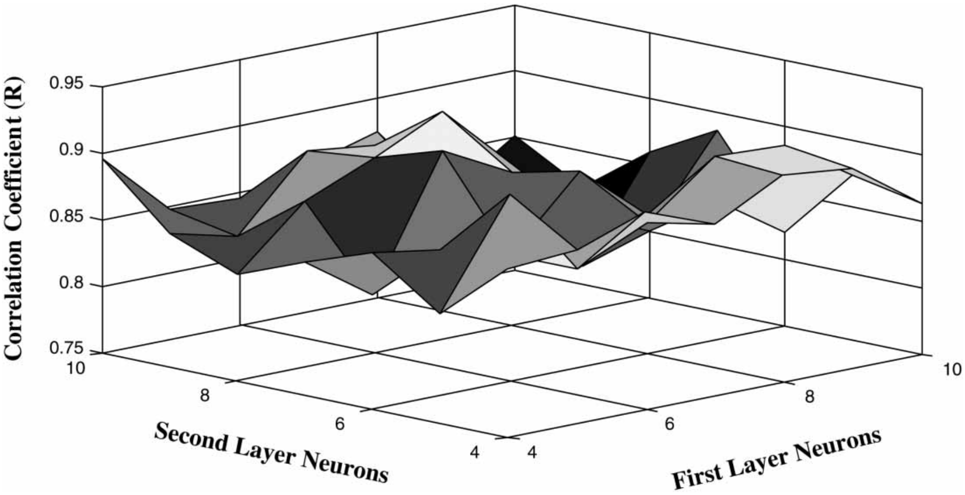

Figure 7 | The correlation value in 3D graph according to total of neurons on first and second layer.

Table 5 | The values for statistical parameters of variables in the ANN model

RMSE	MSE	MAPE	R
0.037	0.03	0.035	0.92

denormalized and the removed values of water demand trend should be added to the predicted values calculated by the neural network. Logarithm taking should also be reversed.

The comparison of ANN-predicted results with the predicted per capita water demand values derived from the Stone–Geary function is shown in Figure 8. Based on preprocessing which was done on input data, the model could nicely predict the overall trend of the future water demand according to the existing trend in descriptive variables. Results showed that taking logarithm increases the accuracy of prediction. According to Figure 8, in monthly water demand values predicted by the MLP, the effects of seasonal changes are visible which are created by the effect of descriptive seasonal changes, and the model also succeeded in dealing with these changes. Results indicate that modeling a time series with an MLP using uncertain components would produce better results. This is thanks to the better scaling of data to allow the ANN to address a wider range. In the second case, taking logarithms improved the results of the model in which the trend was removed from the values.

Therefore, the neural network with the 5:7:8:1 structure, logarithmic preprocessing and trend removal was recognized as the best network. According to the predicted values of independent variables and Figure 8, the per capita consumption for the year 2011 was estimated as 35.53 cubic meters, and for the year 2031 with a 6.48% increase in per capita water demand, the per capita consumption was estimated as 31.79.

CONCLUSION

Knowing the amount of water demand is one of the important and effective factors in water resources management. To date, many reviews have been carried out in the field of water demand forecast but most of these studies have focused on the short-term forecast and have used self-correlation models in forecasting. In this paper, to obtain the relationship between dependent and independent parameters (estimating the demand function) and long-term prediction of urban water demand, MLP was used to predict the long-term water demand. For this purpose, to predict the water demand, effective variables for the period 1997–2008 were collected from the monthly data of Neyshabour City.

Maximum temperature values were predicted from downscaling the model of LARS-WG and under HADCM3 (A1B) scenario for the next 20 years. For this

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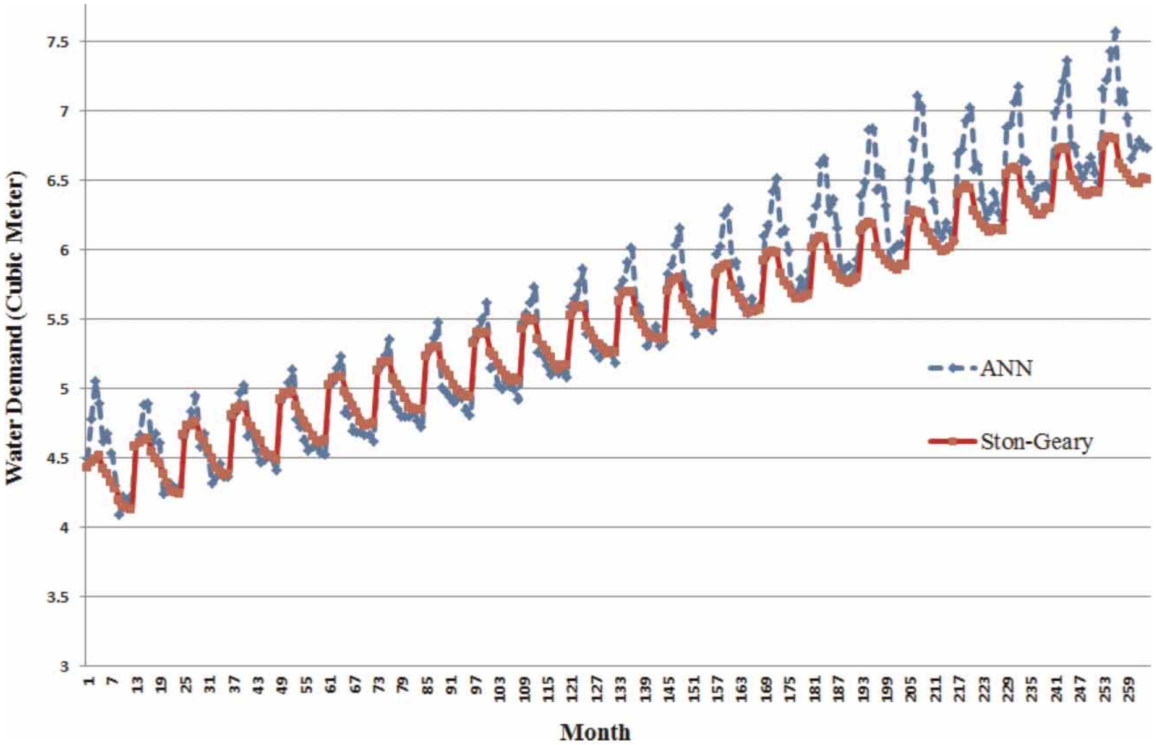

Figure 8 | Comparison between predicted per capita water demand by Stone–Geary model and ANN for the period 2011–2031.

purpose, predicted population values and the number of literate individuals calculated by Pars Consult Co. were used. The predicted values for per capita domestic income, CPI, and the average water price for 2011–2031 were 12, 5, and 15%, respectively. For the long-term prediction using a neural network, a preprocessing should be applied to the data to address the interpolation issue of models. For this purpose, the uncertain component of time series was used in the forecasting process. In the first case, the data trend was omitted, and in the second case, first, logarithm was taken from data and then the trend was removed. With regard to the processed data for both cases, different structures of neural network were examined and, by considering the performance index, the best model was selected in each case, and output parameters were obtained through the selected model; all preprocessing was also reversed in output parameters. To scrutinize the results of modeling with the neural network, the MLP-applied forecasting results for the next 20 years were compared with the results obtained from the regression model, and it was found that the more stationary the data are, the more accurate the neural network model can follow trends and fluctuations.

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