Forecasting the Cost of Water Using a Neural Network Method in the Municipality of Isfahan

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Abstract

Decision making on budgeting is one of the most important issues for executing managers. Budgeting is a major tool for planning and control of projects. In public and non-profit organizations and institutions, estimating the costs and revenues plays an important role in receiving credit and budgeting. In this regard, in the present paper the case of Isfahan municipality is considered. One of the main expenditures of the 14 districts of Isfahan is the costs related to water. Predicting the total cost of water helps the municipality of Isfahan to optimize the water use in its 14 urban zones. Thus, in this study the total cost of water in the districts of Isfahan is estimated using regression analysis and neural network models. Then the results of the methods are compared with each other to minimize the deviations from the approved budget. Finally, the neural network method is selected as the main simulation method for forecasting the total cost of water in the districts of Isfahan.
Keywords: Isfahan Municipality; Regression model; Artificial neural networks; Forecasting; Cost of water; Prediction.

1. Introduction

The exact forecasting of total costs in the organizations which use budgeting for implementing their plans is a main evaluation criterion for managers to achieve their predetermined objectives. In fact, if objectives and costs of plans are estimated well, the objectives could be met. Moreover, a good method to assess managers is to see how much the plans on their hands deviate from the approved budget and expenditures. Clearly, if all expenditures are projected well, deviations from the planned budget and credit would be the least. Thus, in this paper, the cost of municipal water in the municipality of Isfahan is forecasted. As the total cost of water depends on various parameters, the analytical prediction of the total cost is very difficult if not impossible. To estimate the costs, there are a number of methods like traditional techniques which use data on previous periods to estimate costs in the current period and a calculative method involving the use of regression models to estimate costs in the next year. All of the models have both weaknesses and strengths. For example, deviation from the approved budget is a weakness of all estimation methods, which is hopefully not great and serious in the regression methods. In this paper, using a multi-layer perception neural network and an error back propagation algorithm, the total cost of municipal water in the Isfahan municipality is calculated based on some parameters such as per capita population and area of each urban zone. Furthermore, a model for the simulation and prediction of the total annual cost of water in the Isfahan municipality is developed using the regression and the neural network model and the data on water in the municipality of Isfahan from 2004 to 2009. In doing so, the authors mainly aim to know if the estimation of the total cost of water in the 14 urban zones in Isfahan using the artificial neural network does gives greater precision than that of the regression model.

The rest of the paper is organized as follows. In section 2, several studies on the prediction of water use and other fields are presented in order to review different methods of forecasting. In section 3, our new model of forecasting is provided, and its application is elaborated in section 4. Finally, section 5 presents the conclusion.

2. Literature Review

The long-term prediction of consumption was firstly introduced by Wong (1972). Young (1973), Willsie and Pratt (1974) followed the idea and using time series methods, predicted the annual per capita consumption of

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water based on the population, per capita income, price of water, precipitation, temperature, and evaporation. Similarly, Maidment and Parzen (1984) estimated the monthly municipal water use through the time series methods. As a result, they classified the time series values into two categories of permanent and stochastic. Permanent elements included trend and seasonal elements. They modeled the trend elements using the regression between the average annual use of water and the municipal population, and estimated the seasonal elements using the Fourier series. To estimate the stochastic elements, they used two equations: 1) the combination of water usage in the previous days 2) the correlation of the usage with some weather factors such as the maximum temperature in the month, the evaporation, and the precipitation. In another study, Maidment et al. (1985) used a transformation function for predicting the daily usage of water in the city of Texas. Using the time series, they also developed a short-term consumption model in which long-term information was used. Stark et al. (1999) used the artificial neural network models to estimate the short-term usage of water in Alberta, Canada. They predicted the daily usage of water and the usage of water in the next ten days using a number of parameters such as the maximum and minimum temperature, the precipitation in the previous 5 days, the saturation of precipitation in the previous 30 days, indicators representing holidays and non-holidays, and the season in which predictions were done. Some years later, Yu et al. (2002) applied the model developed by Stark et al.'s (1999) to the city of Seoul in South Korea. They used a three-layer neural network in which the maximum temperature, indicators showing holidays or non-holidays, and the water usage in the previous day were used as inputs. In addition to these parameters, the wind speed in spring and the humidity in winter were added as inputs in the corresponding seasons. Liu et al. (2002) used an artificial neural network to forecast the monthly usage of municipal water in the city of Weinam, China. They took account of some economical parameters including per capita income, number of family members, and water price.

More recently, Ghiassi et al. (2008) developed a dynamic artificial neural network model for projecting the urban water demand. They also demonstrated that by using time series water demand data, the dynamic artificial neural network model could provide excellent fit and forecasts without reliance on the explicit inclusion of weather factors. Firat et al. (2009, 2010) investigated the applicability and capability of the three ANN methods including Generalized Regression Neural Networks (GRNN), Feed Forward Neural Networks (FFNN), and Radial Basis Neural Networks (RBNN) for water consumption forecasting from a series of selected independent variables. Sahoo et al. (2009) also examined an empirical model based on ANN, a statistical model (multiple regression analysis (MRA)), and the chaotic non-linear dynamic algorithms (CNDA) to predict the stream water temperature from the available solar radiation and air temperature. In the same vein, Al-Bulushi et al. (2009) developed the ANN models to predict water saturation from the log data in Oman using the wire line logs and core Dean–Stark data. Adamowski (2008) compared multiple linear regressions, time series analysis, and ANNs as techniques for the forecast modeling of the peak of daily water demand in summer. The analysis was performed for 10 years on the peak daily water demand data and meteorological variables (maximum daily temperature and daily rainfall) for the summer months of May to August of each year for an area of high outdoor water usage in the city of Ottawa, Canada.

There are some studies on prediction methods in Iran too. In this regard, the use of artificial neural networks in Iran started in 2000 when the municipal water usage in Yazd was forecasted by some economical parameters as well as the volume of precipitation and evaporation. Likewise, in 2003, using the artificial neural networks, the short-term demand of the municipal water in Tehran, the capital city of Iran, was projected based on the weather-related parameters. Finally, Jalili Ghazi Zade and Noori (2008) predicted the municipal solid waste generation by using ANN in a case study of Mashhad from 2004 to 2007.

The literature review shows that ANN techniques have been commonly used to predict the water resources system including water demand modeling, water consumption, and in a few cases forecasting the cost of water. Therefore, there is a need for comparing ANN techniques with statistical analyses in the field. To this end, the main purpose of this study is to investigate the applicability of the ANN approach and regression analysis to forecasting the annual total cost of water in a case study of the municipality of Isfahan.

3. The Proposed Model

In this section, the proposed model including designing and applying the neural network and regression models is presented. At first, the artificial neural network and its specifications are explained. Then, an indicator is suggested to be used for assessing the performance of the forecasting models. Afterwards, the proposed neural network and regression models are designed. In this regard, different specifications of these models are assigned. Finally, the sensitivity of different parameters involved in forecasting is examined.

3.1 The Artificial Neural Network

An artificial neural network (briefly, neural network) is a data processing system which works like the human brain neural network. In fact, an artificial neural network is a mathematical model of the human being neural cells. In an artificial neural network, information is presented in a large number of simple elements called neurons.

Information signals are transformed among neurons by connection chains. Each connection chain has weights which multiply by every signal passing that chain. In addition, each neuron has an activation function which applies to the neuron input (each neuron input is the weight summation of input signals) to generate the output signal.

A neural network model usually has a number of layers which are formed by neurons. One of the most important features of the neural network is its learning ability. The neural network behaves like a small set of human brain cell which uses the experience for the present decision makings. In fact, learning in the neural network is the calculation of connection weights. To learn the neural network, a series of training data including an input vector and an output vector are used. In the process of training a neural network, connection weights are calculated in a way that the neural network can generate an output vector with a certain error value. One of the most important training algorithms is the error back propagation method which is applied in the present research. Basically, there are two kinds of learning methods: 1) supervised learning and 2) unsupervised learning. In the supervised learning, the values of objective variables are known. Therefore, the error of forecasting can be calculated easily. Then, using different algorithms of training such as error back propagation, network weights are adjusted to minimize the prediction error. The error of prediction is either the summation of errors or the average of absolute errors. According to Figure 1 which shows how a neural network model works, training data are inputted to the neural network. Starting with the initial weights of the connections, the outputs are calculated by the weights summation and operating the activation function. While the real outputs are known, the difference between the calculated output values and the resulted output values indicates the error. Since the neural network operates in a way that minimizes the error as much as possible, the weights are adjusted. This process goes on until the final weights which lead to a small error are obtained.

In this research, the multi-layer perceptron artificial neural network and error back propagation methods are applied. The error back propagation algorithm is applied to train a multi-layer perceptron neural network. The training data must be used as input to the neural network with a suitable structure. Also, after training by using the simulation of real values and output values, the network performance is evaluated. The higher the number of the input data is, the better the network is trained.

To create a structure for a neural network, the number of inputs, the number of hidden layers, the number of neurons in the end layer, the number of output neurons, and activation functions of neurons should be determined (Vogelset al., 2005). Modeling and approximating the functions using the neural networks do not need the system equations because a neural network only uses numeral values of inputs and outputs and considers the system as a black box. The input and output data used in training can be obtained by any method such as simulation or experimental measurements.

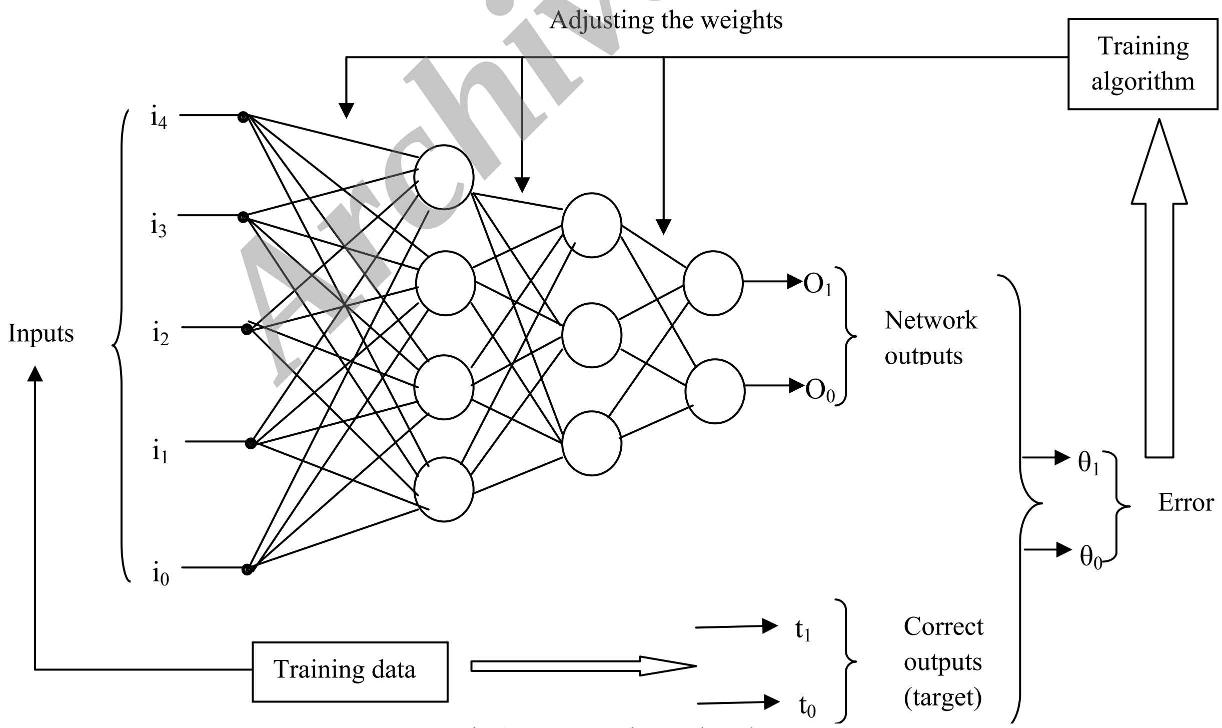

Fig. 1. How a neural network works

The strength of a neural network lies in its learning ability which enables it to extend its knowledge. Generally, what distinguishes learning from memorizing is the ability to extend the current knowledge and initial information (Wong, 1972; Firat et al., 2010). Figure 2 shows a multi-layer neural network model which uses the error back propagation algorithm.

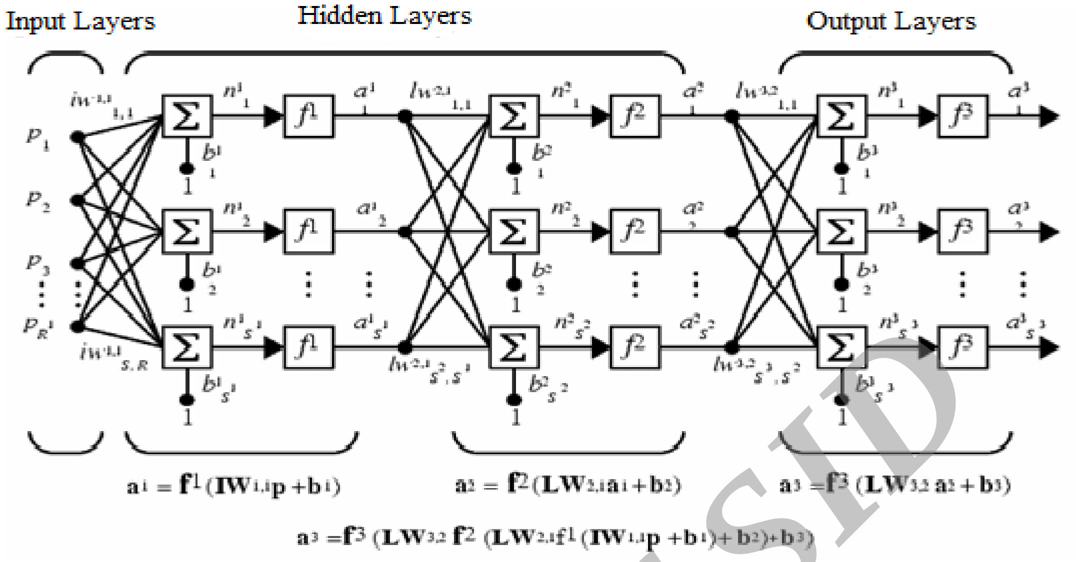

Fig. 2. Structure of an artificial neural network using the error back propagation algorithm

3.2. Evaluation indicators of the model

Since there are a large number of models for forecasting, models with the most compatibility with the reality should be selected. Such models can approximate the costs with the minimum error. Therefore, models and their results should be assessed to see if a model with regard to its training data can result in acceptable outputs with new input data. There are different methods of evaluation among which the mean absolute percentage error (MAPE) method is used in this paper. The MAPE which has been applied by many researchers is defined as follows (Chen et al., 2003; Song et al., 2003):

$$MAPE = \frac{100}{n}\sum_{i=1}^{i=n}\frac{|realvalue - forecastedvalue|}{realvalue} \qquad (1)$$

where *n* indicates the number of data points.

3.3. Developing the neural network model

As mentioned before, the neural network models are created for modeling and forecasting the cost of water. They have the following specifications:
1) The neural networks can approximate almost every function,
2) The neural networks can be matched automatically. In other words, when the relation between statistical information does not change, the neural networks update their levels,
3) The neural networks are more stable than other prediction methods,
4) To use the neural networks, learning about complex methods is not needed, and just statistical information is required,
5) Due to the text processing feature of the neural networks, wrong statistical variables do not affect results.

Numerous algorithms have been applied to train the neural networks. One of the most important training algorithms is the error back propagation algorithm which is used in this paper. The error back propagation is a complimentary part of the topology of forward multi-layer networks. In addition to the error back propagation method, multi-layer perception networks which are able to identify the pattern and function of a complex problem are applied. MATLAB 6.1 which is equipped with the neural network module is also used. The neural network module, embedded in MATLAB, has a user-friendly graphical interface and can develop neural networks with different structures in the least amount of time. As the present study needs to develop a large number of neural network methods, MATLAB is appropriate.

In modeling the neural networks, it is advised that before training, weights of the neural networks be assigned with small and stochastic values. This would train the network better. In MATLAB, this could be done by checking a choice. It should be noted that if weights are trained by different initial values, the neural network models with the same structure and training vectors do not provide the same results.

There are two unknowns in modeling the neural network:

1. the structure of the neural network which is the number of layers, neurons of each layer, and activation functions,

2. The input parameters of the model.

To select the best structure for neural networks, the only choice is to examine all possible structures through trial and error. In this research, a large number of models are built and examined. The modeling has started from the simplest structures and gradually the number of neurons and layers has increased.

In this paper, the activation function of hidden layers is selected as the non-linear form of the transformation function of Tangent-Sigmoid. The main reason for selecting this function is that the non-linearity of the parameters of water cost can be modeled well with this non-linear function (Akesson and Toivmen, 2006; Shamimet al., 2004).

3.3.1. Architecture of the proposed neural network

Architecture of a neural network has an important role in understanding the relations in the network. According to the problem, the number of inputs in the network is three and the number of output layer equals to one. To achieve the best architecture for the neural network, different architectures are developed and examined. A network with two layers, five neurons in the first layer (hidden layer), one neuron in the second layer (output layer), the transform function of Tangent-Sigmoid for the first layer, and the linear transform function for the second layer is designed. Figure 3 illustrates the structure of the neural network model. As you see, the applied neural network model has three layers. Moreover, Figure 4 shows the graphs of the two activation functions, linear and Tangent-Sigmoid.

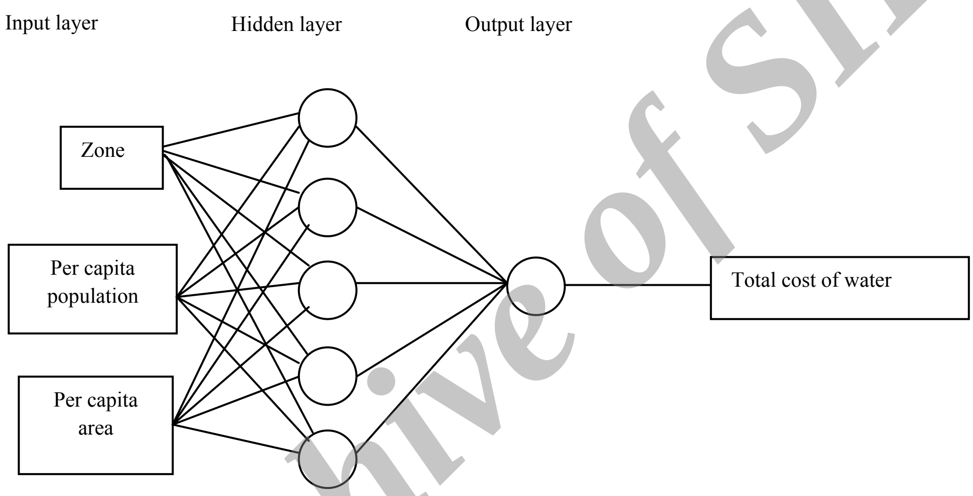

Fig. 3. Architecture of the proposed network

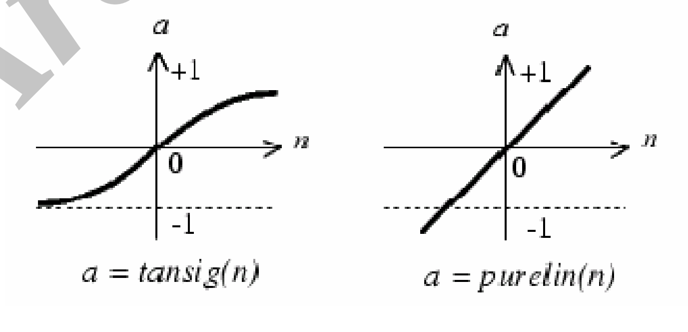

Fig. 4. The activation functions used in the network

3.3.2. Forecasting by using an artificial neural network

The neural network calculates the municipal water cost as a function per capita area and population. To design the neural network, firstly the best initial values for the network are selected. Then, the network is trained and examined. The indicators for evaluating and measuring the precision of the network are chosen as MAPE. To obtain the optimum number of epochs in the training process, the network was trained 50 to 500 epochs.

3.4. Forecasting by using linear regression

To evaluate the results of the artificial neural network, it is necessary to model the prediction problem using linear regression. The independent variables of linear regression are per capita population and per capita area and zone while the dependent variable is the cost of water (Draper and Smith, 1973; Rodkov and Yordanova, 2008; Msiza et al., 2008).

3.5. Examining and selecting the input parameters of the model

To forecast the total cost of municipal water usage in the 14 urban zones of the city of Isfahan, the zones should be studied well. The total cost of municipal water in Isfahan include: 1) the cost of water used in the houses, and 2) the cost of water used in the offices. Various factors influence the total cost of water. These factors include water parameters such as temperature, precipitation, air pressure, wind speed, daytime hours, humidity, and social and economical factors such as the quality of people's lives, per capita income, population, area, culture, water price, and quality of the water distribution system. The quality of the water distribution system itself includes some factors like the water distribution network, network management, and management of consumption.
Selecting the input parameters of the model, two main factors should be considered: 1) variables that have a major influence on the municipal water cost in each urban zone of Isfahan should be selected, 2) statistical information of the variables should be available as inputs to the model.

To examine the effects of the parameters, which are grouped into two classes based on year and zone, on the total cost of water, the following sensitivity coefficient is used:

$$S_{ij} = \frac{\delta_{yi}}{y_i} \div \frac{\delta_{xj}}{x_j} \quad (2)$$

The sensitivity coefficient which changes between -1 and +1 is a mathematical indicator that shows the relation between two variables. If the sensitivity coefficient is zero, variables are not correlated. The positive sensitivity coefficient means that two variables change in the same way while the negative sensitivity coefficient indicates that two variables change in the reverse way. To calculate the sensitivity coefficient of the data, SPSS is used. The results show that the effects of different parameters on the total cost of water vary greatly.

The precision of a model highly depends on the correlation between input and output variables. Table 1 below indicates different variables and the sensitivity coefficients between each pair of variables. According to the table, per capita income and area and per capita green space are selected as the input parameters. It should be noted that experts usually consider a parameter whenever its sensitivity coefficients either in year or in zone are close to 0.5.

Table 1
The sensitivity coefficient of the data

Row	Effective parameter	Urban zone	Year	Effect of zone	Effect of year
1	Population	0.278	0.477	×	✓
2	Area	0.011	-	×	×
3	Per capita population	0.522	0.926	✓	✓
4	Per capita area	0.678	0.926	✓	✓
5	Price	-	-	×	×
6	Average annual temperature	-	-0.334	×	×
7	Average annual precipitation	-	-0.359	×	×
8	Present budget	0.411	-0.333	✓	×
9	Construction budget	0.344	-0.333	×	×
10	Holiday	-	-0.26	×	×
11	Total area of green space	0.503	0.333	✓	×
12	Per capita daily garbage	0.234	-	×	×
13	per capita cost of street cleaning per citizen	-0.172	-	×	×

4. Implementation of the Proposed Model

In this section, the modules are designed. In the first module, the total cost of water is estimated using the two parameters of per capita population and per capita area. In this model, the data on these parameters from 2004 to 2009 are used as inputs. To evaluate the model, the obtained values of the model and the real values corresponding to 2007, 2008, and 2009 are presented in Table 2. The value of MAPE for each year is also calculated. As the data on per capita green space from 2004 to 2008 were not available, another model is developed in which the total cost of water is predicted based on three parameters: per capita population, per capita area, and per capita green space. The results of this model are also reported in Table 2. To evaluate this model, MAPE is used as well. Besides, Figures 5 to 7 show the trends of the forecasted values of the cost of water in Isfahan's 14 zones using the neural network and the corresponding real values from 2007 to 2009. It should be mentioned that these figures and tables do not show the values which are obtained from considering the per capita green space parameter in the neural network modeling. Table 3 presents the values of MAPE for the three years of 2007, 2008, and 2009 in the neural network model when the parameter per capita green space is not considered. In addition, Table 4 shows the comparison between the forecasted and the real values of the cost of water in 2008 when the neural network model considers the per capita green space parameter. Figure 8 illustrates the trends of the forecasted and the real values of the cost of water in Isfahan's districts in 2008 when the neural network considers the parameter of per capita green space. Then Table 5 indicates the value of MAPE for forecasting the cost of water in 2008.

Table 2
The artificial neural network model without the parameter of per capita green space

Urban zone	water cost 2004	water cost 2005	water cost 2006	Real value 2007	Forecasted value 2007	Real value 2008	Forecasted value 2008	Real value 2009	Forecasted value 2009
1	30	20	30	27.612	31.775	30	29.458	50	63.707
2	30	49	32	7.498	9.443	16	28.589	35	32.636
3	50	45	47	54.597	63.886	65	54.611	52	50.809
4	109	160	127	145.97	144.486	99	103.081	165	157.237
5	125	270	170	123	113.139	230	232.33	165	162.691
6	115	60	120	103.987	126.147	100	102.423	150	172.837
7	30	52	45	25	25.882	50	51.616	82	76.873
8	120	180	50	30.496	31.576	30	33.918	30	33.773
9	8	12	12	5.226	8.12	13	13.371	35	77.214
10	10	10	17	18.648	11.454	55	86.275	54	53.37
11	6	32	14	10.687	12.339	20	20.13	12	10.961
12	-	-	-	14.892	4.6	16	33.667	70	51.017
13	-	-	-	-	-	37	31.692	17	13.162
14	-	-	-	-	-	-	-	65	61.24
Total	633	890	664	567.613	582.847	761	821.161	982	1017.527

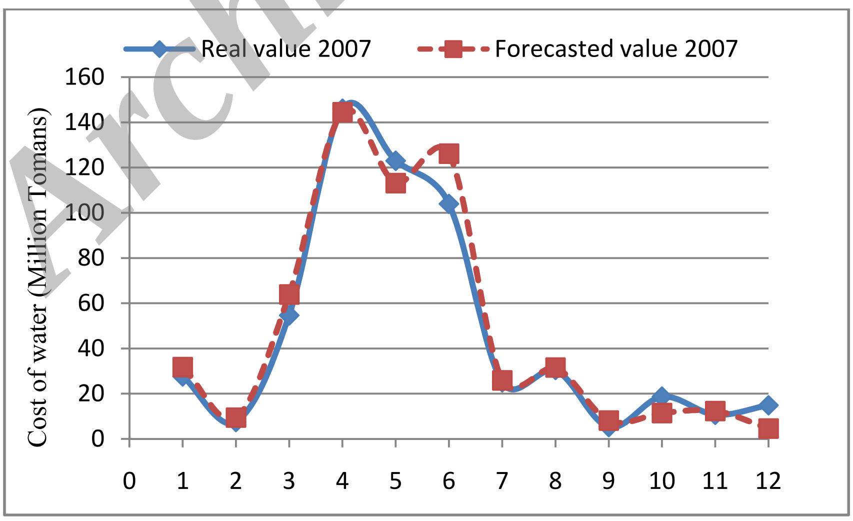

Fig. 5. The neural network model without per capita green space in 2007

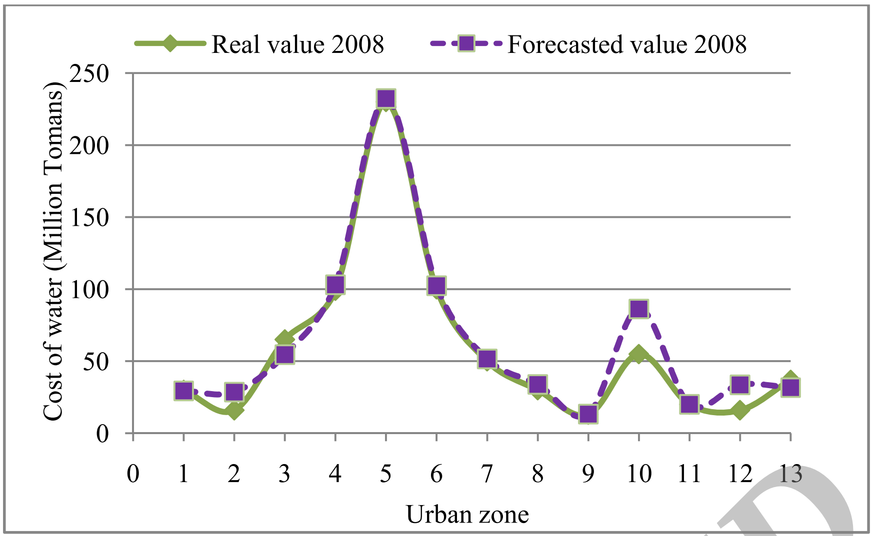

Fig. 6. The neural network model without per capita green space in 2008

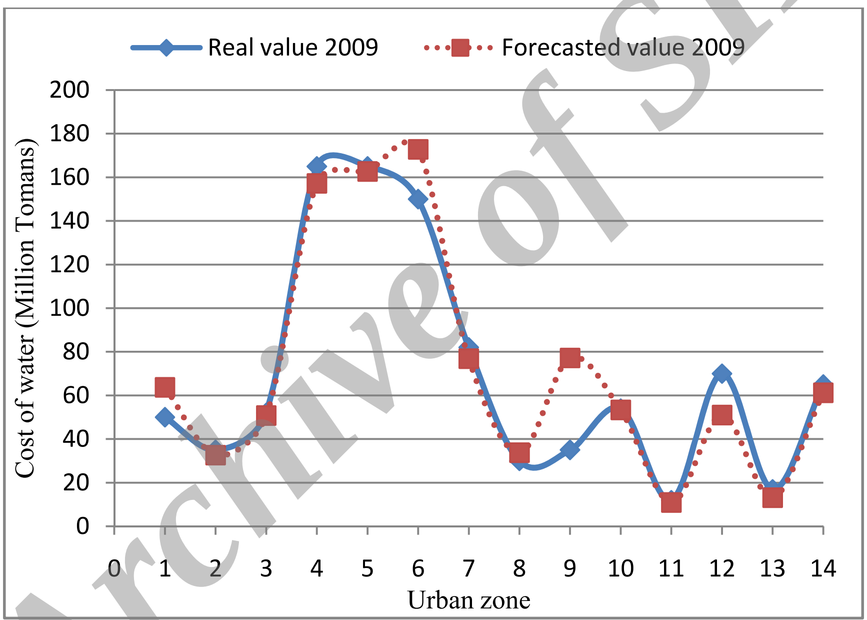

Fig. 7. The neural network model without per capita green space in 2009

Table 3
Evaluation of the neural network model without per capita green space

Year	Mean absolute percentage error (%)
86	19
87	16
88	12

Table 4
The neural network model with per capita green space

Urban zone	Real value 2008	Forecasted value in 2008 with per capita green space
1	30	29.994
2	16	16
3	65	64.997
4	99	98.991
5	230	230.027
6	100	100.461
7	50	49.439
8	30	30.036
9	13	12.985
10	55	46.329
11	20	20.011
12	160	159.732
13	37	45.973

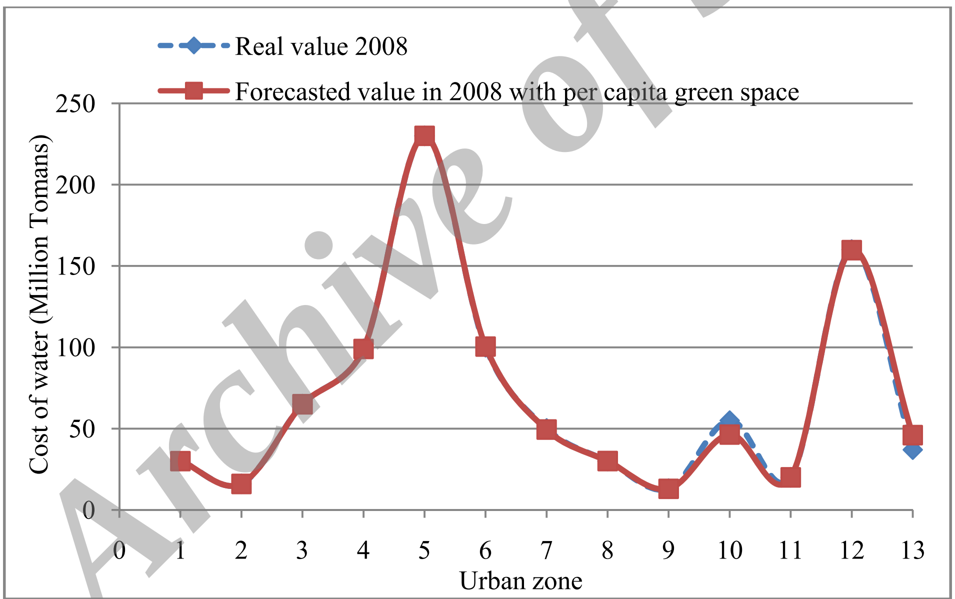

Fig. 8. The neural network model with per capita green space

Table 5
Evaluation of the neural network model with per capita green space

Model	Mean absolute percentage error (%)
Forecasted value in 2008 with per capita green space	3

Now to evaluate the results of the neural network model, a linear regression model is developed to forecast the cost of water. The independent variables of the linear regression model are as follows:

1. Per capita population
2. Per capita area
3. Urban zone

In addition, the dependent variable of the linear regression model is the cost of water. To assess the models, the mean absolute percentage error indicator is used. Table 6 reports the results of forecasting the cost of water from 2004 to 2009 using the regression model. Figures 9 to 11 also show the trend of the forecasted values, using linear regression, for the cost of water in

Isfahan's 14 urban zones, and the corresponding real values from 2007 to 2009. Then Table 7 indicates the values of indicator MAPE for the results of the regression model from 2007 to 2009.

Table 6
Results of the regression model

Urban zone	Water cost 2004	Water cost 2005	Water cost 2006	Real value 2007	Forecasted value 2007	Real value 2008	Forecasted value 2008	Real value 2009	Forecasted value 2009
1	30	20	30	27.612	24.933	30	31.931	50	73.801
2	30	49	32	7.498	10.27	16	16.153	35	57.421
3	50	45	47	54.597	42.793	65	61.95	52	47.845
4	109	160	127	145.97	144.601	99	94.788	165	168.218
5	125	270	170	123	81.068	230	198.369	165	148.491
6	115	60	120	103.987	125.796	100	119.163	150	184.736
7	30	52	45	25	18.278	50	38.523	82	68.366
8	120	180	50	30.496	3.754	30	12.5	30	12.606
9	8	12	12	5.226	9.549	13	21.911	35	60.065
10	10	10	17	18.648	10.801	55	38.411	54	37.471
11	6	32	14	10.687	28.853	20	47.958	12	26.883
12	-	-	-	14.892	17.507	16	184.972	70	72.134
13	-	-	-	-	-	37	51.208	17	25.189
14	-	-	-	-	-	-	-	65	67.687
Total	633	890	664	567.613	518.203	761	917.837	982	1050.913

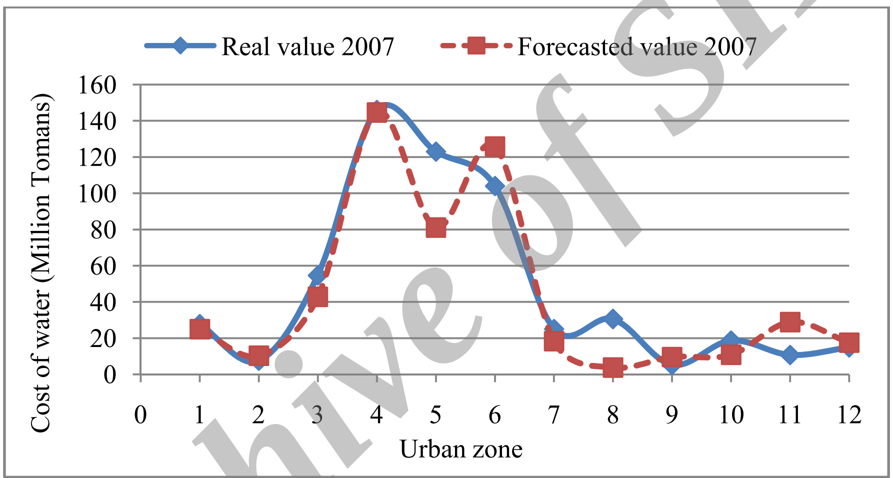

Fig. 9. Results of the regression model for 2007

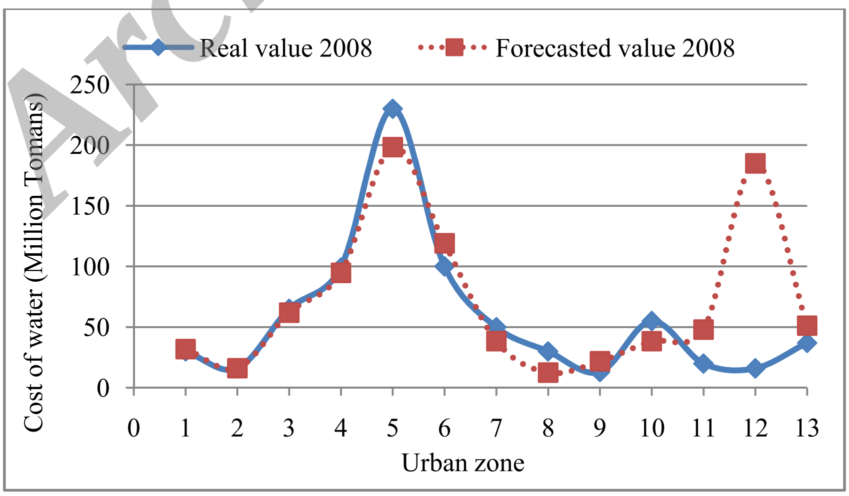

Fig. 10. Results of the regression model for 2008

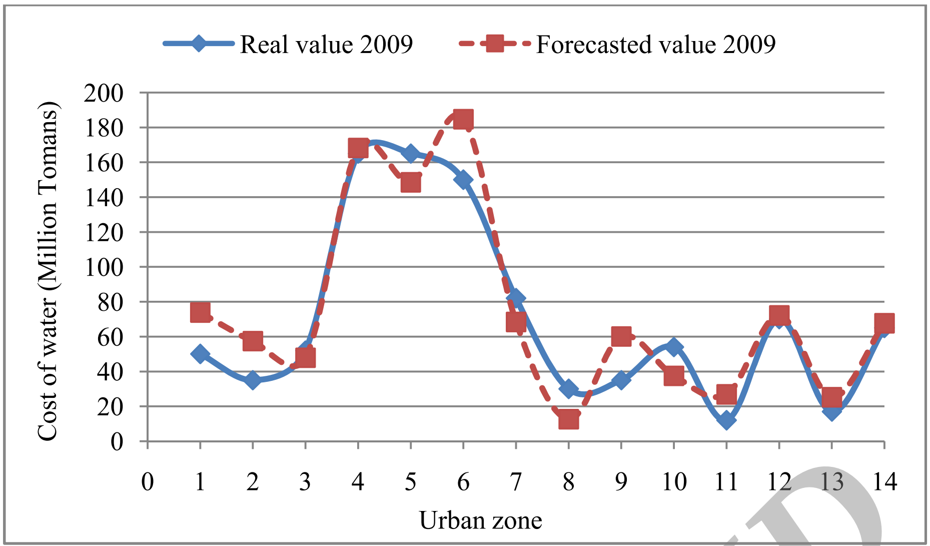

Fig. 11. Results of the regression model for 2009

Table 7
Evaluation of the regression model

Year	MAPE (%)
86	33
87	22
88	24

Table 8
Results of the sensitivity analysis

Urban zone	Range of per capita population	Range of per capita area	Effect of per capita population on cost in corresponding urban zone (Ci)	Effect of per capita area on cost in corresponding urban zone (Di)
1	0.1	0.001	7.4	8.33
2	0.1	0.001	5.81	17.5
3	0.1	0.001	11.2	13
4	0.1	0.001	12.51	17.74
5	0.1	0.001	15.68	12.13
6	0.1	0.001	10.47	17.85
7	0.1	0.001	15.35	16.73
8	0.1	0.001	23.07	21.42
9	0.1	0.001	7.099	21.87
10	0.1	0.001	19.63	23.47
11	0.1	0.001	6.15	12
12	0.1	0.001	12.96	58.33
13	0.1	0.001	11.87	18.27
14	0.1	0.001	15.47	19.11

The effects of the two parameters, per capita area and per capita population in each urban zone, on the total cost water in each urban zone should be examined. In this regard, the results of the sensitivity analysis are shown in Table 8 and Figures 12 to 14.

5. Conclusion and Future Research

In the present study, the total cost of municipal water in the districts of Isfahan is simulated and forecasted using an artificial neural network. The findings reveal that the neural networks are very capable of understanding and simulating patterns of water cost, and thus can be used as a strong tool for forecasting the cost of water. In addition, three parameters of per capita population, per capita area, and per capita green space have the greatest effect on the total cost of water in the municipality of Isfahan. Yet, there is not a sufficient amount of data on the per capita green space, therefore two neural networks were designed and applied in the study. The results of these networks indicate that if there were enough data on the per capita green space, the neural network model with the three

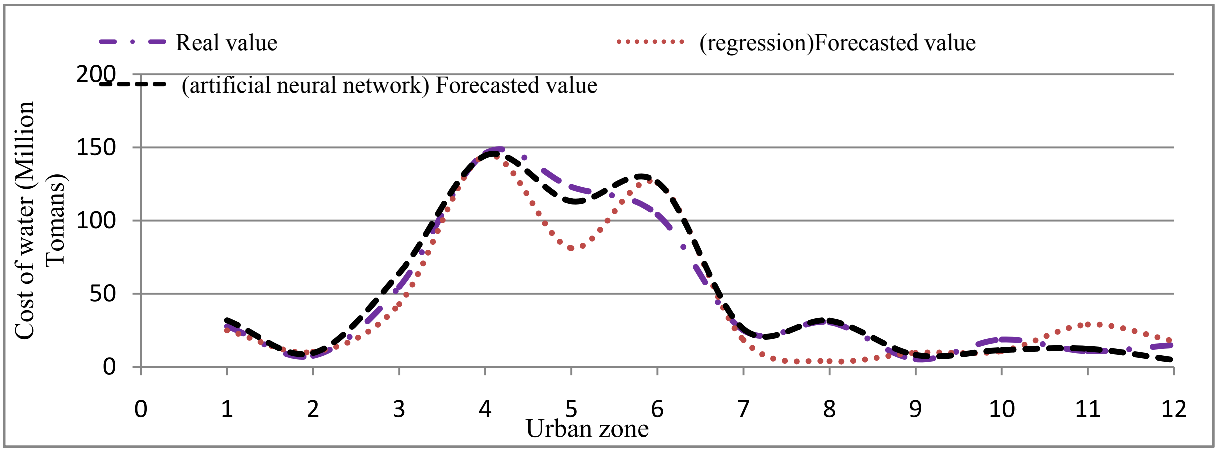

Fig. 12. Comparison of the regression model and the neural network for forecasting the cost of water in 2007

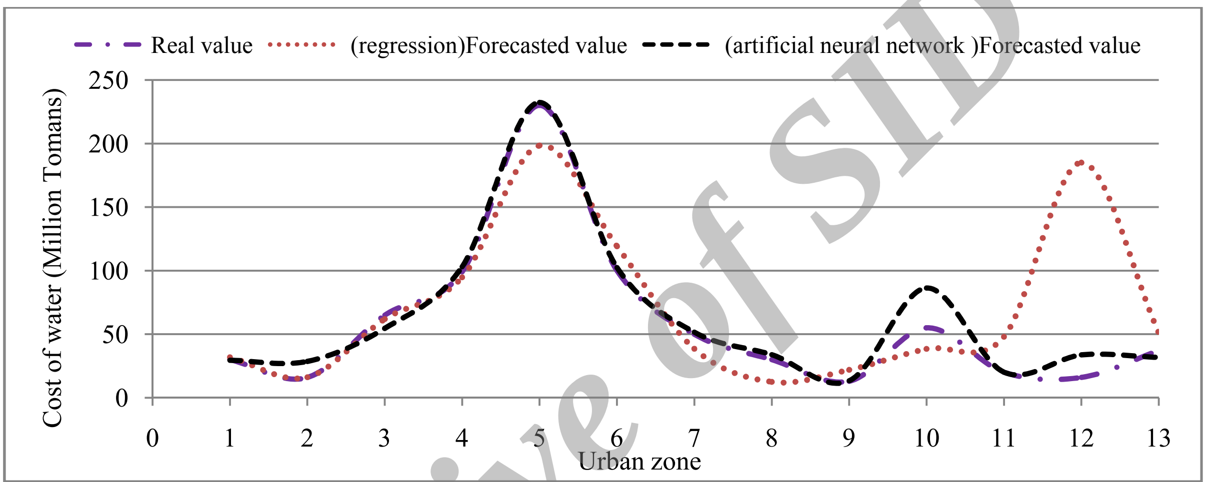

Fig. 13. Comparison of the regression model and the neural network for forecasting the cost of water in 2008

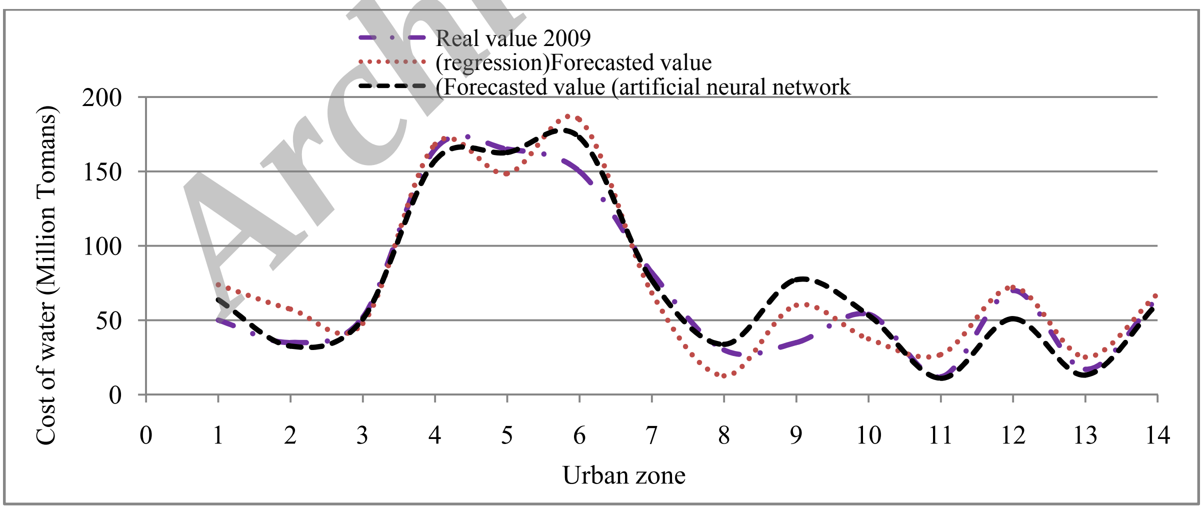

Fig. 14. Comparison of the regression model and the neural network for forecasting the cost of water in 2009

parameters would be the best model for forecasting the total cost of water in the 14 urban zones of Isfahan. Finally, the results demonstrate the superiority of the neural network models over the regression models in predicting the cost of water.

For further research, some applications of the neural network in Isfahan municipality may be investigated. These applications are as follows:

1. Replacing the statistical and classic methods with the proposed model in this research

2. Using simulation models in forecasting and optimization
3. Nonlinear modeling
4. Management and planning
5. Developing projects and measuring the risks of projects
6. Project control and management

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