European Water 58: 481-487, 2017.

Domestic water demand forecasting for Makkah, Saudi Arabia

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Abstract: The prediction of water demand is important in countries that have less water resources. Water demand forecasts assist water utility managers in taking decisions on additional supply acquisition, treatment infrastructure, water use restrictions, water conservation impacts, price elasticity and demand management. The aim of this paper is to develop an Artificial Neural Network (ANN) models for predicting annual and monthly domestic water demand in Makkah city, Saudi Arabia. The variables that were selected for development the water demand prediction models were: household area (m^2), city population, average personal income, average maximum temperature, and average number of visitors. This data between the years 2002 and 2012 were collected from the relevant sources. The number of dataset was eleven on annual basis and 132 on monthly basis. An ANN approach using feed forward backpropagation was developed to predict monthly and annual domestic water demand in relation to the selected variables. The study revealed that the ANN water demand models can predict monthly and annually water demand with a mean square error (MSE) between 0.0006 and 0.0002, and models' efficiency (E) between 0.97348 and 0.94626. In conclusion, it is suggested that a further development of the proposed ANN models are required to generalize and apply the proposed models to other cities in Saudi Arabia.

Key words: Makkah, water demand, artificial neural network, prediction, domestic water, water consumption

1. INTRODUCTION

A successful management of the water utility requires a careful balance of available water supply to meet the required water demand. Water demand forecasts help water utility managers to take decisions regarding additional supply, water treatment extension, water use restrictions, water conservation impacts, price flexibility and demand management (Billings and Jones, 2008). There are several factors that could impact water demand, including population, employment, technology, weather, climate, price, infrastructure efficiency, conservation programs, socioeconomics, and water awareness. However, many of these variables are difficult to quantify and have a high degree of uncertainty (Billings and Jones, 2008). It has been suggested that the threat of increasing water demand greatly outweighs other consequences of climate variability including variations in the hydrologic cycle in defining the status of global water systems (Vorosmarty et al., 2000). Therefore, it is absolutely necessary to increase the skill and usability of current water demand modelling efforts.

Extensive studies in water demand have been conducted since the 1960's with a primary focus on aggregate municipal demand or residential demand. Most research on water demand use an economic modelling approach that attempts to utilize water price and socio-economic variables such as covariates in statistical models for water demand (Arbués et al., 2003). Many studies have emphasized the use of price elasticities and income for water demand forecasting (Katzman, 1977). Such econometric models have been used to forecast water demand and have been expanded to incorporate price and incomes using traditional and generalized least squares technique (Katzman, 1977; Malla and Gopalakrishnan, 1997; Babel et al., 2007). Multiple regression models to analyze sustainable water consumption (Coles & Simiu, 2003) have been developed and recently socioeconomic indicators have been incorporated into these models (Babel et al., 2007). Discrete/continuous choice models have been created and found to have increased price elasticity when used (Hewitt and Hanemann, 1995). Most recently, a study was conducted by Ajbar and Ali (2015) to predict water demand in Makkah city, Saudi Arabia using Artificial Neural Network.

The main water resources in Saudi Arabia are divided into four categories namely underground, surface, desalinated, and treated wastewater. The main source of surface water in the south-western region is the rainfall. Dams are used to store surface water in some regions of the Kingdom. The Ministry of Water and Electricity (MOWE) built approximately 230 dams in the country to store runoff water (Al-Zahrani, 2009). According to Al-Ibrahim (1990), underground water is classified into renewable and non-renewable resources, where approximately 30% of the non-renewable resource has been utilized in 1995 (Al-Turbak and Al-Dhowalia, 1996).

This paper mainly aims at predicting the monthly and annually water demand in Makkah city, Saudi Arabia. The proposed annual water demand model could be utilized for future development plans consideration; especially capital expenditures and water quantities. However, the monthly water demand model is important for municipal authorities to improve monthly water production quantities.

2. METHODOLOGY

2.1 Makkah City, case study

Makkah city is situated in the Southern part of Saudi Arabia, about 70 km from Jeddah, and 277 m above the sea level; exactly at 21°25′0″N 39°49′0″E. The total area is over 1,200 km^2. The city population in 2012 was about 1.7 million, whereas visitors during Hajj period are more than triple this number every year. It has an extremely arid climate, with warm temperature in winter, which range from 18 °C at night to 30 °C in the afternoon, and summer temperatures range between 30 °C to 40 °C, and some rains between November and January.

2.2 Data collection

The following variables were selected for the development of water demand prediction models: household area (m^2) (Schleicha and Hillenbrand, 2009), city population (Ajbar and Ali, 2015), average personal income (Vorosmarty et al., 2000; Ajbar and Ali, 2015), average maximum temperature (Ajbar and Ali, 2015), and average number of visitors (Ajbar and Ali, 2015; Griffin and Chang, 1990). The data between the years 2002 and 2012 were collected from the relevant sources. The selection of these variables in this period of time was limited by the historical data availability. The data on water demand and consumption were collected from the Ministry of Water and Electricity. The data on household area, population, personal income, and number of visitors was collected from the Ministry of Planning and Pilgrimage. Data on the temperature was available from the local weather authority. The data was monthly for the following parameters: domestic water demand (m^3), visitors (capita), and temperature (°C), while the yearly data was collected for the household area (m^2), personal income (USD), and population (capita) parameters.

2.3 Development of ANN models

MATLAB mathematical software version 7.11.0 (R2010b) was used as a tool to develop Artificial Neural Network (ANN) models for the prediction of Makkah city's water demand (m^3) on monthly and yearly basis. Initially, the data was set between 0 and 1 in order to achieve minimum mean square error (MSE) estimation.

The following subsections describe the methods and algorithms used during models development.

2.3.1 Database description

The collected dataset was divided into input and target matrixes. The input variables for predicting the yearly water demand as a target were household area, city population, average personal income, average maximum temperature, and average number of visitors per year. While, for predicting the monthly water demand as a target, the input variables were household area, city population, and average personal income on yearly basis, as well as maximum temperature and number of visitors on monthly basis. The number of dataset was eleven annually and 132 on monthly basis. Initially, the entire dataset was randomized to prevent the biases and to create representative sections of the datasets for training and testing (Abushammala et al., 2014). Subsequently, the dataset was divided into training and testing subsets. In ANN modelling, one fifth of the dataset was used in the testing stage due to its smaller size.

2.3.2 Basic considerations

In this study, a feedforward (newff) network with an input layer, a hidden layers, and an output layer was used. The log-sigmoid transfer function (logsig) was used between all layers at all developed networks. According to Sablani (2007), there are two modes for learning a network; a supervised and an unsupervised. The supervised back-propagation is the most popular training algorithm (Abrahart et al. 2004; Rene and Saidutta, 2008). Therefore, scaled conjugate gradient (trainscg) back-propagation algorithm was used in this study for training the networks. The training process between both input and expected output was repeated until the performance error decreased to an acceptable level, and the internal connection weights were modified in response to the computed error. For a single iteration, the error is calculated and the summed errors from overall neurons are divided by the size of data used in the training process to estimate average MSE. The maximum number of training epoch, the performance error goal, and the momentum factor were set to be 104, 10-4, and 0.92, respectively (Abushammala et al., 2015).

3. RESULTS AND DISCUSSION

3.1 Selection of training algorithm

Five backpropagation training algorithms were used to determine the best training algorithm for the gathered data. For all algorithms, a three-layered approach with a log-sigmoid transfer function (logsig) at a hidden layer and an output layer was used. In addition, 20 and 4 neurons were used in the hidden layers respectively for the monthly and annually basis as initial values for all backpropagation algorithms. The momentum was a constant 0.92 for all the algorithms used. The testing phase results with different backpropagation training algorithms are provided in Table 1. Compared to other backpropagation algorithms, Levenberg-Marquardt (trainlm) was the best algorithm, producing the lowest MSE, and was associated with the highest efficiency (E) value in the testing phase which has been calculated according to Abushammala et al. (2014). Using the Levenberg-Marquardt algorithm resulted in a decrease of up to 10 % of the MSE produced compared with using the Powell-Beale conjugate gradient algorithm, which was the algorithm that produced the second lowest MSE (Table 1). Subsequently, the Levenberg-Marquardt algorithm was considered for training the final ANN water demand model for both basis.

3.2 Optimization of neuron numbers

Optimization of neural network neuron numbers is an important task in developing the best ANN model. Therefore, the optimum network neuron numbers were investigated in the current study for both monthly and annual ANN models to improve the estimation performance of both models. The number of hidden layer chosen was one, similar to the initial ANN structure. The Levenberg-Marquardt backpropagation training algorithm was used for training different ANN models with different neuron numbers at hidden layer. The neurons number in the hidden layer was varied between 15 and 25 for the monthly model, while number of neurons in the hidden layer of the yearly model varied between 2 and 4. The optimal number of neurons in the hidden layer for both models was chosen based on the lowest MSE, and the highest *E* value in the testing stage.

Table 1. Comparison of backpropagation algorithms

Backpropagation algorithms	Function	MSE	*E*
Levenberg-Marquardt backpropagation[a]	trainlm	0.0009	0.7384
Scaled conjugate gradient backpropagation	trainscg	0.0011	0.6969
BFGS quasi-Newton backpropagation	trainbfg	0.0066	0.6535
One step secant backpropagation	trainoss	0.0105	0.6197
Powell-Beale conjugate gradient backpropagation	traincgb	0.0010	0.7194

[a] *Best training algorithm*

The logistic sigmoid transfer function was used at all layers during the training phase, while the value of momentum was a constant of 0.92 (Abushammala et al., 2015). The results show that the 3 neurons in the hidden layer produced smaller MSE and higher *E* value compared with other models on the annual basis (Table 2). However, the monthly model with 15 neurons in the hidden layer produced smaller MSE and higher *E* value in contrast to other models (Table 2).

Table 2. Performance of different models tested in both ANN models with a varying number of neurons in the hidden layer

Models	Training stage		Testing	
	MSE	E	MSE	E
Annually models				
[5 4 1]	0.00056807	0.97526	0.0042437	0.86425
[5 3 1][a]	0.00060915	0.97348	0.0018152	0.94193
[5 2 1]	0.00058961	0.97433	0.0028277	0.90955
Monthly models				
[27 25 12]	0.00092600	0.75486	0.014561	0.43348
[27 20 12]	0.00017441	0.95383	0.0058722	0.77153
[27 15 12][a]	0.00020299	0.94626	0.0040575	0.84214

[a] *Best neuron number*

Figures 1 and 2 show the optimized ANN structure, the linear regression between the targets of the water demand data and the ANN model outputs in the training phases, the number of epoch during the training phase, and comparison between the real and the predicted values from the ANN for both annual and monthly water demand models. The optimum annual ANN training process took 7 epochs (Fig. 1) to reach the error goal (10^{-6}), while the optimum monthly ANN training process had taken 9 epoch to reach the same error value (Fig. 2).

Figures 1 and 2 show that the target data exhibited slight large variations during the comparison between the target data and the estimated values in the training and the testing phases. However, it was evident that the ANN models' outputs were reasonable and they simulated the target data in both figures.

The correlation coefficient (*R*) value found in this study was relatively higher than some of those reported in the literature; a coefficient of determination of 0.90 for prediction of the quantitative characteristics of water bodies (Palani et al., 2008). However, some previous studies achieved *R* value up to 0.99 (Elmolla et al., 2010). The relatively low values of *R* and *E* of the ANN water demand models obtained by this study might be attributed to data noise, due to the small sample size of the dataset.

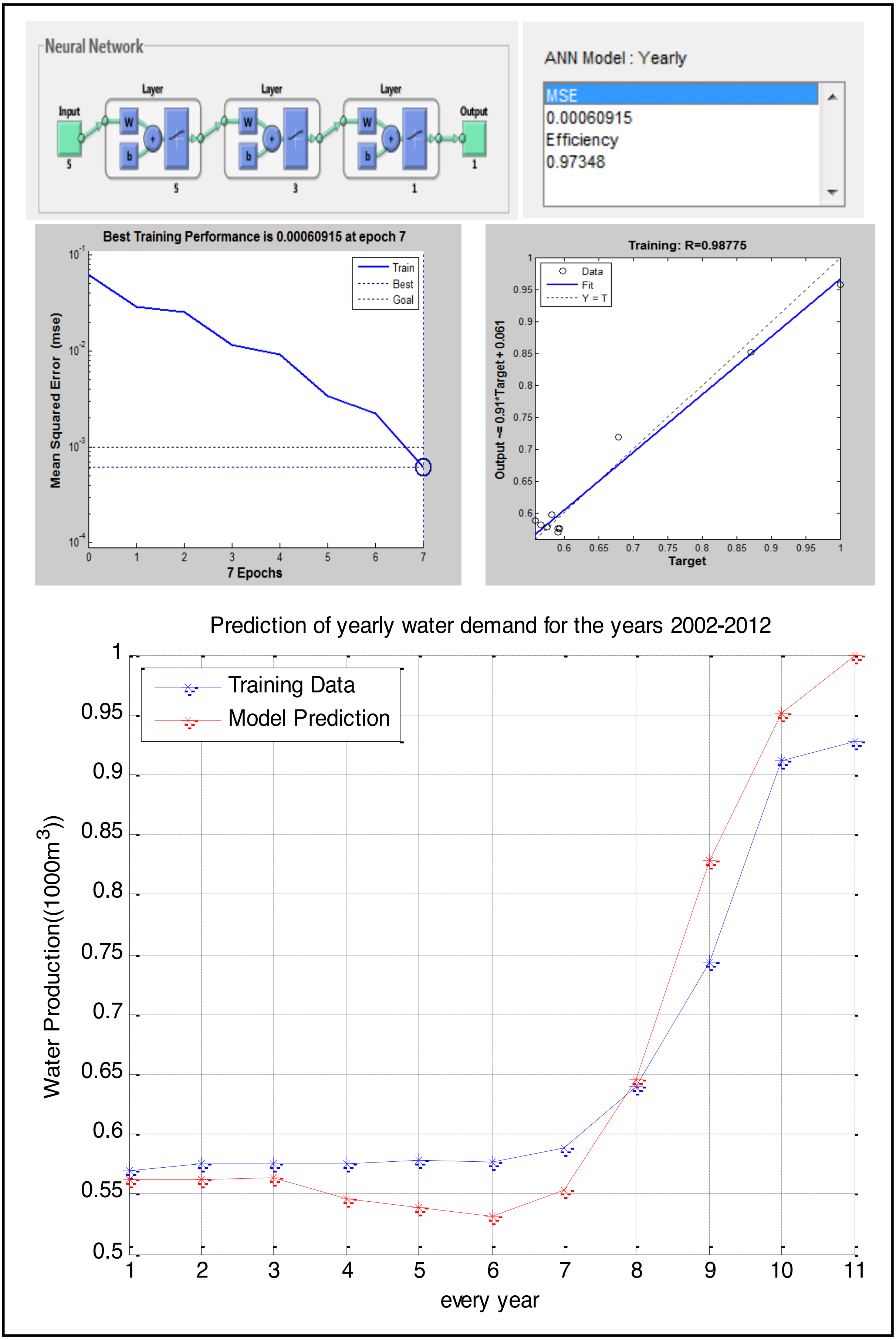

Figure 1. ANN structure, training, and testing performance of the annually model

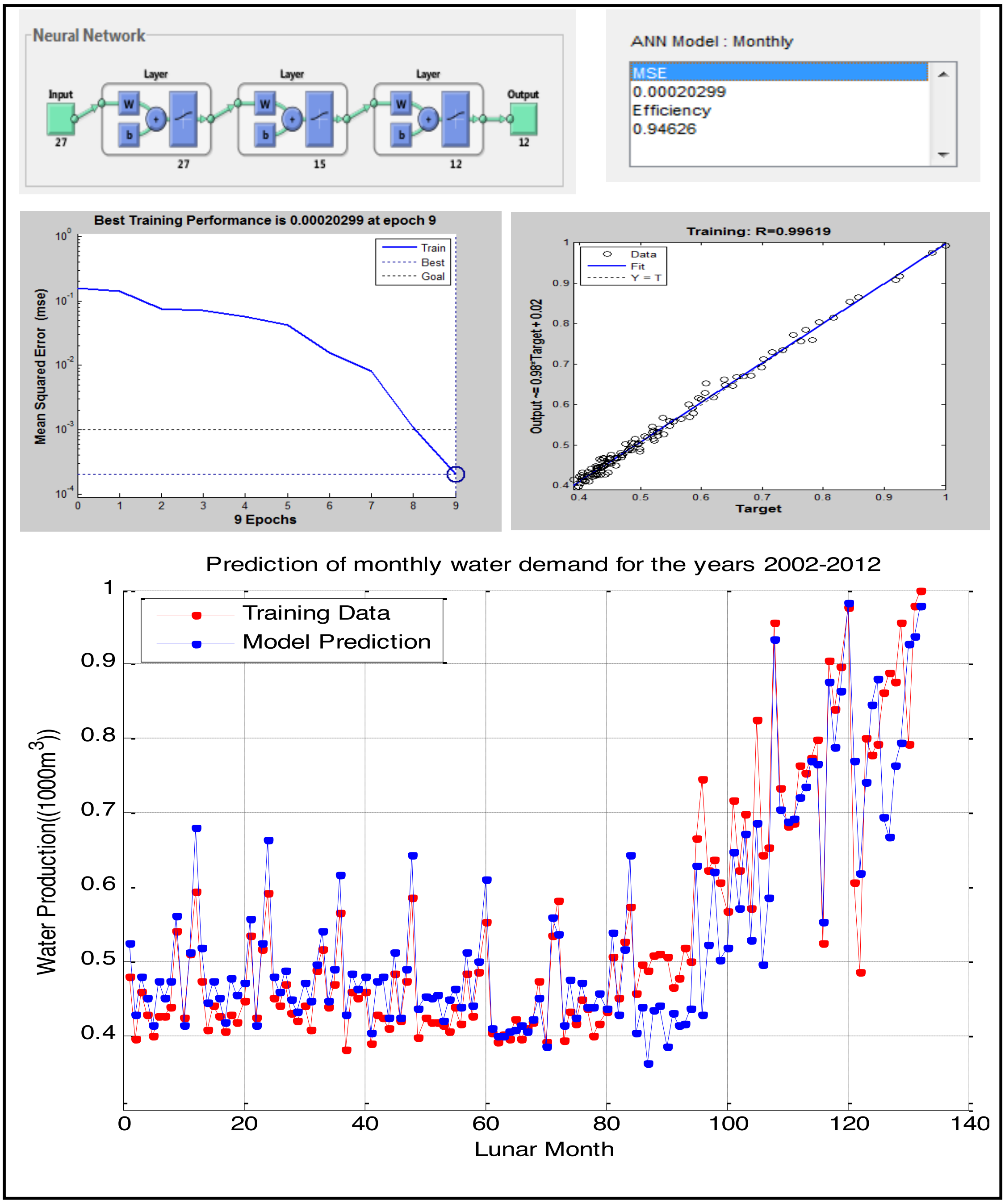

Figure 2. ANN structure, training, and testing performance of the monthly model

4. CONCLUSION

This study aimed to develop a water demand model for predicting monthly and annual water demand in Makkah city, the most visited city in Saudi Arabia for pilgrimage. The analysis of historical data (2002-2012) revealed that most of the selected variables in this study were positively influenced by the water demand. The data also demonstrates a steady annual increment in the water demand; 1888 m^3 in 2002 to 18888 m^3 in 2012. The main conclusions of the study were as follows:

1. The selected variables in this study were all important at different levels for prediction of water demand in Makkah city.
2. ANN prediction models developed in the current study can be used for monthly and yearly water demand estimation in Makkah city and could be optimised and could even be used in other cities in the country.

ACKNOWLEDGEMENT

The authors are grateful to the Ministry of Water and Electricity (MOWE), Ministry of Planning and Pilgrimage, and the weather authority for providing the data needed to complete this research.

REFERENCES

Abrahart, R.J., Kneale, P.E., See, L.M., 2004. Neural networks for hydrological modeling. London: Taylor and Francis Group plc.

Abushammala, M.F.M, Basri N-E.A., Elfithri, R., Younes, M.K., Irwan, D., 2014. Modeling of methane oxidation in landfill cover soil using an artificial neural network. Journal of Air and Waste Management Association, 64: 150-9.

Abushammala, M.F.M., Basri, N-E.A., Younes, M.K., 2015. Landfill Methane Oxidation: Predictive Model Development. Journal of Applied Sciences, 15: 283-288.

Ajbar, A., Ali, E.M., 2015. Prediction of municipal water production in touristic Mecca City in Saudi Arabia using neural networks. Journal of King Saud University-Engineering Sciences, 27: 83-91.

Al-Ibrahim, A.A., 1990. Water Use in Saudi Arabia: Problems and Policy Implications. Journal of Water Resources Planning and Management (ASCE), 116: 375-388.

Al-Turbak, A.S., Al-Dhowalia, K.H., 1996. Contribution of Treated Wastewater in Solving Water Shortage Problems in Saudi Arabia (in Arabic), King Saud University. Symposium on Wastewater Treatment Technology and Reuse, Riyadh, 14-33.

Al-Zahrani, K.H., 2009. Sustainable Development of Agriculture and Water Resources in the Kingdom of Saudi Arabia, Conference of the International Journal of Arts and Sciences, 1: 3-37.

Arbués, F., García-Valiñas, M.A., Martínez-Espiñeira, R., 2003. Estimation of residential water demand: a state of the art review. The Journal of Socio-Economics, 32: 81-102.

Babel, M.S., Das Gupta, A.D., Pradhan, P., 2007. A multivariate econometric approach for domestic water demand modeling: An application to Kathmandu, Nepal. Water Resources Management, 21: 573-589.

Billings, R. B., Jones, C. V., 2008. Forecasting Urban Water Demand, Second Edition. American Water Works Association, Denver, CO.

Coles, S., Simiu, E., 2003. Estimating Uncertainty in the Extreme Value Analysis of Data Generated by a Hurricane Simulation Model. Journal of Engineering Mechanics, 129: 1288-1294.

Elmolla, E.S., Chaudhuri, M., Eltoukhy, M.M., 2010. The use of artificial neural network (ANN) for modeling of COD removal from antibiotic aqueous solution by the Fenton process. Journal of Hazardous Materials, 179: 127-134.

Griffin, R.C., Chang, C., 1990. Pre-test analyses of water demand in thirty communities. Water Resources Research, 26: 2251-2255.

Hewitt, J.A., Hanemann, W.M., 1995. A Discrete/ Continuous Choice Approach to House hold Water Demand under Block Rate Pricing. Land Economics, 71: 173-192.

Katzman, M.T., 1977. Income and price elasticities of demand for water in developing countries. Water Resources Bulletin, 13: 47-57.

Malla, P.B., Gopalakrishnan, C., 1997. Residential water demand in a fast-growing metropolis: the case of Honolulu, Hawaii. International Journal Water Resources Development, 13: 35-51.

Palani, S., Liong, S.Y., Tkalich, P., 2008. An ANN application for water quality forecasting. Marine Pollution Bulletin, 56: 1586-1597.

Rene, E.R. Saidutta, M.B., 2008. Prediction of BOD and COD of a refinery wastewater using multilayer artificial neural networks. Journal of Urban and Environmental Engineering, 2: 1-7.

Sablani, S.S., 2007. Artificial neural network modeling. In Handbook of food and bioprocess modeling techniques, ed. Sablani, S.S., Datta, A.K., Rehman, M.S. Mujumdar, A.S. London: Taylor & Francis Group, LLC, 375-403.

Schleicha, J. Hillenbrand, T., 2009. Determinants of residential water demand in Germany. Ecological Economics, 68: 1756-1769.

Vorosmarty, C.J, Green, P., Salisbury, J., Lammers, R.B., 2000. Global Water Resources: Vulnerability from Climate Change and Population Growth. Journal of Science, 289: 284-288.