International Journal of Academic Engineering Research (IJAER)
ISSN: 2643-9085
Vol. 7 Issue 3, March - 2023, Pages: 1-9

Models for forecasting water demand: A case study of Oman

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Abstract: *Water resource management systems are indispensible tools for provision of adequate water services across towns, municipalities and cities. This study attempts to develop and compare three variants of artificial neural networks to predict monthly water demand using socio-economic and demographic data of Oman. The results showed that the cascade forward neural network outperformed Elman and feed forward neural networks. It is envisaged that these water demand foresting models would provide useful and relevant information to top managers to make operational, tactical and strategic decisions to meet the demand for water supply efficiently.*

Keywords—water demand, water supply, population, forecasting models

1. INTRODUCTION

Accurate water demand forecasting has become indispensible tools in the efficient operation, management and planning of water supply systems to meet the future needs of the end users [1]. Water demand forecasting could be categorized into two types: long term; and short-term forecasting. The essence of long-term water demand forecasting is to design new water distribution networks or expand the existing ones while the short-term water demand forecasting is an important process to operate and manage an existing water distribution network efficiently and effectively. Water utility managers depend on accurate short-term forecast to ensure that there is no shortage of water supply to the public or over-production of potable water which would increase operational cost, wastage nd increasing need for storage capacity if demand is incorrectly estimated [2].

Furthermore, low precipitation, very limited water sources and aging infrastructure in most countries have increased the need for demand management as an alternative option to enable the municipalities provide adequate and suitable water services to the public. Thus, accurate short-term forecasting of water demand helps to optimize water supply systems and implement effective water demand management initiatives. In addition, effective water demand management aids a better understanding of the dynamics and salient factors influencing urban water consumption. It supports effective maintenance management and operational schedules for reservoirs, storage tanks, pumps and piping networks. It equates the need for water supply by the utility companies and demand by residential, commercial and industrial users [3].

Water demand has been predicted using traditional approaches of analyzing times series water consumption data and statistical models with a range of input data. The key limitation of these forecasting techniques is that they require large number of independent variables and a general assumption that the measured or observed data are linear and stationary. In reality, the pattern of water demand is a non-stationary, stochastic time series that may include a nonlinear trend in the mean, non-constant variance and discontinuities [4]-[6].

Water demand is a subjective event. It is difficult to build deterministic models using conventional modeling techniques for it. In addition, it is a challenging problem to estimate accurately water demand due to numerous factors such as dynamic users' behaviour or characteristics, changing weather conditions, public policies, technological and demographic characteristics that influence it [4]. In order to develop forecasting model for short-term water demand, socio-economic and climatic data are the common dataset for this task. The essence of using socio-economic and demographic data is to account for the impact of the structural development of rapidly growing geographical locations that may not be easily represented in the time series data [5].

The grey-box or machine learning techniques are often applied by researchers to develop water demand models [6]. In one of the previous studies, Ref. [7] investigated the short term water demand process based on the total weekly water demand, total weekly rainfall and weekly average maximum air temperature from the city of Kanpur, India. The ANN models consistently outperformed the regression and time series models developed in this study. Reference [8] compared the performance of generalized regression neural networks, feed forward neural network and radial basis neural networks to forecast monthly water consumption from socio-economic and climatic data of Izmir, Turkey. The results indicated that generalized regression neural network outperforms the two other methods in modeling monthly water consumptions. In [9], the results of the study showed that neuro-fuzzy models produced better results than the fuzzy and ANN models to predict Tehran water consumption.

Furthermore, the study performed by [10] examined multi-linear regression, Levenberg-Marquardt ANN, resilient ANN and Power-Beale ANN models to model peak weekly water-demand forecast in Nicosia, Cyprus using climatic variables and past water demand. It was found that Levenberg-Marquardt ANN method had the most accurate prediction compared to the other ANN and multilinear regression (MLR) models. Reference [11] applied machine learning methods to predict the future water demand in an urban area of a city in south-eastern Spain. Based on the city data, experimental comparison of six models was carried out. The results of this study identified support vector regression models (SVR) as the most accurate model over multivariate adaptive regression splines, Projection pursuit regression and Random forests.

In [5], dynamic artificial neural network was proposed to forecast water demand based on the data obtained from San Jose retail water company, California, USA. The proposed dynamic ANN outperformed the ARIMA and feed forward back propagation network across all time horizons. Further studies in [1] explored hybrid wavelet–bootstrap–artificial neural network (WBANN) modeling approach for urban water demand forecasting. Climate and water demand data for almost three years obtained from the city of Calgary, Alberta, Canada were used in this study. The performance of WBANN models was found to be better when compared with that of standard artificial neural networks (ANN), bootstrap-based ANN (BANN), and wavelet-based ANN (WANN) models.

In spite of the efforts by various scholars in the literature to develop accurate water demand models using artificial neural networks, the use of cascade forward, feed forward and Elman neural networks to forecast water demand especially in arid regions with very little precipitation and very limited natural fresh water sources has not been extensively studied. The main focus of this study is thus to examine the performance of these neutral networks in short-term water demand forecasting using the socio-economic and climatic variables. This paper presents a unique contribution to knowledge as it attempts to perform comparative analysis of water demand modeling based on these three variants of ANN modeling techniques.

This study is made up of four sections. Section two presents a brief overview of Oman and data employed for the study. In addition, model development and structures, and performance criteria are introduced in section two. Section three discusses the data analysis and results of the study. Finally, the last section concludes the study.

2. MATERIALS AND METHODS

2.1 Study Area

Oman is one of the countries situated in the Middle East North Africa (MENA) region with hot and arid climatic conditions. The land surface area of Oman is dominated by Hajar mountains (approximately 14%), desert (approximately 83%) and coastal areas (approximately 3%). The main economic activities are undertaken in the coastal areas of Oman. It is rich in hydrocarbons with a GDP of three hundred billion dollars. The total population of Oman is estimated to be more than five million people. The average water demand per year in Oman is estimated as 1872 million cubic metres (MCM). On the average, an individual in Oman consumes not less than 160 liters of water per day [12]-[13].

It is a country that is highly dependent on rainfall to recharge its groundwater and for its fresh water supplies. Rainfall is limited and changes considerably throughout the country. The mean annual rainfall is estimated as 19,250 MCM. The key source of water supply in Oman is groundwater. The domestic, municipal and industrial water supplies are obtained from the desalination plants in Oman. Agricultural use accounts for more than 80 percent of the total water use in Oman for irrigation of farms and livestock production during the hot summer season. The industrial sector, mostly oil and gas sector accounts for more than 7 percent of the water consumption while 10 percent is estimated as water consumption for domestic consumption in Oman. The strategies to increase water supply in Oman focused on water harvesting, desalination and wastewater reclamation and reuse [13].

Furthermore, due to deteriorating groundwater quality and declination of its level, the gap between the water demand and supply is being addressed through supplies from desalinated water treatment plants. Water desalination was introduced in Oman to meet the rapid demand for domestic water in the country. The country has also invested in wastewater treatment plants to reclaim and reuse wastewater for recreational activities, irrigation of landscaped areas and parks. In Oman, there is a deliberate strategy to reduce water losses in the water supply system in order to conserve water use. Also, there is restriction imposed by Omani Government to control well drilling unless permit is granted [13]. Based on the need for effective water conservation policy to fill the gap between water supply and demand in Oman, the performance of ANN models to forecast the water demand is proposed in this study.

2.2 Data for the Study

Water demand is a non-linear and complex process. Most conventional forecasting techniques demonstrate unsatisfactory performance and do not provide accurate and reliable results. It is assumed in this study that monthly water consumption, $WC(t)$ is a function of immediate past monthly water consumption $WC(t-1)$, average monthly temperature $TP(t)$, average monthly humidity $HD(t)$, population $PL(t)$, gross national product growth $GG(t)$ and inflation rate $IR(t)$. The function showing the relationship between the water consumption and the input variables is expressed as:

$$WC(t) = \left(WC(t-1), TP(t), HD(t), PL(t), GG(t), IR(t)\right) \quad (1)$$

International Journal of Academic Engineering Research (IJAER)
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Therefore, in this study, artificial neural network techniques for water demand forecasting models, a total of 82 months data samples for each variable were collected between the period of January 2004 and January 2019 for the country of Oman. The data covered population, Gross Domestic Product, inflation rate, rainfall or precipitation, temperature, humidity and were sourced from World Bank and Weather Underground websites [14]-[15].

The data set was divided into two parts, training, and testing data set. The training data set and testing data set were 75% and 25% respectively. Tables 1 and 2 show the statistical parameters of the dataset such as minimum and maximum values, mean, standard deviation, skewness and Kurtosis of each input and output variables.

Table 1: Statistical parameters for training data sets

Variables	Max	Min	Mean	St dev	Skew-ness	Kur-tosis
WC (m^3)	2.22 x 10^7	3.74 x 10^7	3.04 x 10^7	3.77 x 10^6	-0.07	2.23
TP (degree Celsius)	21	36	28.82	4.20	-0.26	1.83
HD (%)	40	81	60.01	10.03	0.07	2.74
PL (Number of people)	4.03 x 10^6	4.92 x 10^6	4.52 x 10^6	2.67 x 10^4	-0.19	1.84
GG (%)	-0.32	5.05	2.52	1.86	0.19	1.45
IR (%)	0.06	1.59	0.88	0.42	-0.09	1.89

Table 2: Statistical parameters for testing data sets

Variables	Max	Min	Mean	Std dev	Skew-ness	Kur-tosis
WC (m^3)	3.21 x 10^7	4.24 x 10^7	3.80 x 10^7	2.62 x 10^6	-0.09	2.38
TP (Degree Celsius)	21	34	27.92	4.16	-0.11	1.57
HD (%)	40	87	64.48	10.92	-0.28	3.05
Population of people)	4.94 x 10^6	5.19 x 10^6	5.07 x 10^6	7.82 x 10^4	-0.08	1.79
GG (%)	-3.2	3.399	-1.04	1.76	1.08	3.38
IR (%)	-0.90	0.93	-0.13	0.49	0.32	2.36

2.3 Artificial Neural Networks

2.3.1 Feed forward Neural Network

Feed forward neural network (FFNN) is made up of input layer, one or more hidden layers and an output layer of computational nodes or neurons. The input layer receives input signals that propagate through the intermediate or hidden layer(s) to the output layer on a layer-by-layer basis. The schematic diagram of a feed forward neural network is shown in Fig. 1. A neuron is the basic unit of the neural network. It performs both combining and activation functions. All neurons apart from the neurons in the input layer act as summing unit for all input signals as well as propagating the signal through a non-linear or activation function. The connections between the neurons are organized designated as weighted synaptic connections. The coefficients of the linear combinations plus the biases are called the weights. These nodes and synaptic weights work together using a large set of simple functions to define or establish complex relationship between the input and output dataset. An algorithm is needed to train the synaptic weights in order for the neural network to slide through the local minima and converge very fast.

The layers of the feed forward networks are fully interconnected. That is, each computation nodes in each layer is connected to every node in the previous and succeeding layers. However, the nodes in the same layer are not connected or linked to each other [1]. The mathematical equation of the FFNN can be written as [16]:

$$y = f^{o}\left(\sum_{j=1}^{k}\omega_j^{o} f_j^{h}\left(\sum\nolimits_{i=1}^{n}\omega_{ji}^{h}x_i\right)\right) \tag{2}$$

Where f^{o} is the activation function on the output layer and f_j^{h} is an activation function on the hidden layer and if a bias is added to the input layer and the activation function of each neuron in the hidden layer is f^{h} then equation (1) becomes

$$y = f^{0}\left(\omega^{b} + \sum\nolimits_{j=1}^{k}\omega_j^{0} f^{h}\left(\omega_j^{b} + \sum\nolimits_{i=1}^{n}\omega_{ji}^{h}x_i\right)\right) \tag{3}$$

Where ω^{b} is the weight from bias to output and ω_j^{b} is the weight from bias to hidden layer.

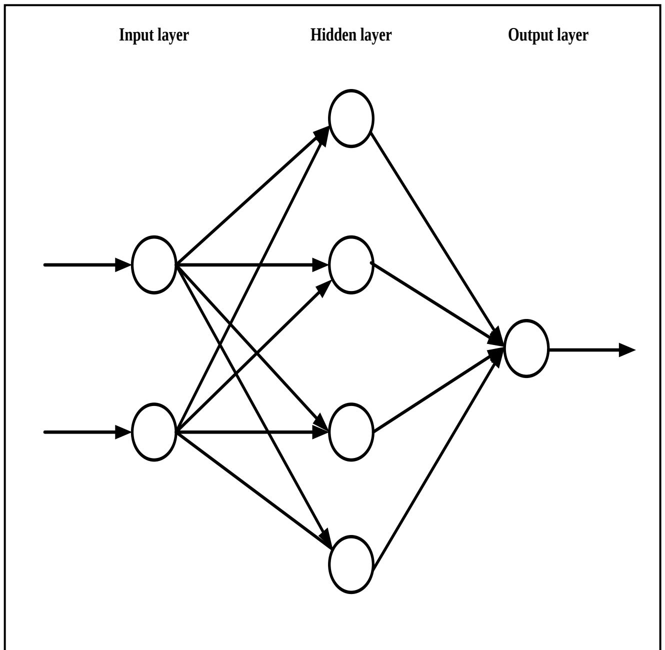


Fig. 1 Structure of feed forward neural network

2.3.2 Cascade Forward Neural Network

The cascade forward neural network (CFNN) has a structure that is similar to the feed forward neural network. However, the input signal in the network is connected to each hidden layer of the network through the network matrix as shown in Fig 2. It has a weight connection from the input to each layer and from each layer to the successive layers [17]. Although, this structure increases the complexity of the training process, it however supports the non-linear mapping ability of the network. In addition, the structure makes the actual output of the network to be closest to the expected output in term of the smallest mean square error. The back-propagation algorithm is used to train and optimize the weight and bias matrix of the network just like the feed forward network [18]. The mathematical expressions of the model can be stated as follows:

$$y = \sum_{i=1}^{n} f^{i}\omega_{i}^{i}x_{i} + f^{0}\left(\sum_{j=1}^{k}\omega_{j}^{o} f_{j}^{h}\left(\sum_{i=1}^{n}\omega_{ji}^{h}x_{i}\right)\right) \qquad (4)$$

Where f^{i} is the activation function from the input layer to the output layer and ω_{i}^{i} is weight from the input layer to the output layer. If a bias is added to the input layer and the activation function of each neuron in the hidden layer is f^{i} then equation (2) becomes

$$y = \sum_{i=1}^{n} f^{i}\omega_{i}^{i}x_{i} + f^{0}\left(\omega^{b}\sum_{j=1}^{k}\omega_{j}^{o} f^{h}\left(\omega_{j}^{b} + \sum_{i=1}^{n}\omega_{ji}^{h}x_{i}\right)\right) (5)$$

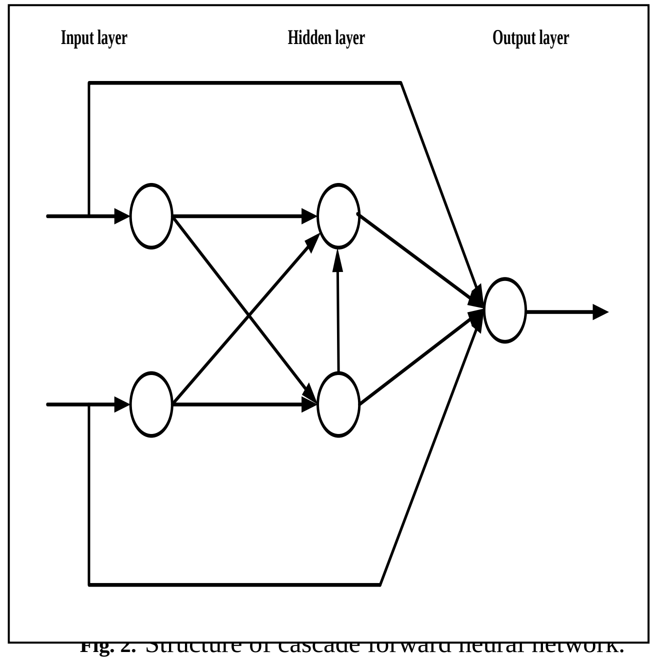


Fig 2 Structure of cascade forward neural network

2.3.3 Elman Neural Network

Elman neutral network (ELNN) is referred to as a partial recurrent network. The outputs of the hidden layer are allowed to feed back into itself through a buffer referred to context layer. It is a special kind of feed-forward neural network with short term memory neurons and local feedback. It can learn, recognize and generate temporal and spatial patterns. The architecture of recurrent neural network is different from that of feed forward network from the point of view that there is at least one feedback loop. In recurrent network, it is possible for one layer to have feedback connections as well as neurons with self-feedback connection where neuron's input is from its output as shown in Fig 3. The learning capability is thus affected by the feedback loop present in the network.

Furthermore, these feedback loops entail the use of unit delay elements that lead to non-linear dynamical behavior. The non-linear dynamics plays an important role in the storage function of recurrent networks. Recurrent networks are sensitive and can be adapted to past input. Elman neural network have modifiable feed forward connections and fixed recurrent connections. It has certain unique dynamic characteristics over static neural networks. The connections consist of feed-forward connections with delay elements. The input layer is divided into two parts: input units and context units. The context units hold a copy of the activations of the hidden units from the previous time step. The Elman neuron network has hidden layer with enough neurons and output layer. There are adjustable weights lining in each adjacent layer. It is generally described as a feed-forward network with additional memory neurons and local feedback. The selfconnections of the context nodes in the Elman network enable them to be very useful for modelling of dynamic systems [19].

Mathematically, the output $y_i(t)$ can be calculated using the weighted sum of its input as expressed in (6)

$$y_i(t) = f\left(\sum_{j=1}^{i} \omega_{ji} h_j(t)\right) \tag{6}$$

Where f is the transfer function, w_{ji} is the connection's weight between the j^{th} hidden unit h_j and the i^{th} output.

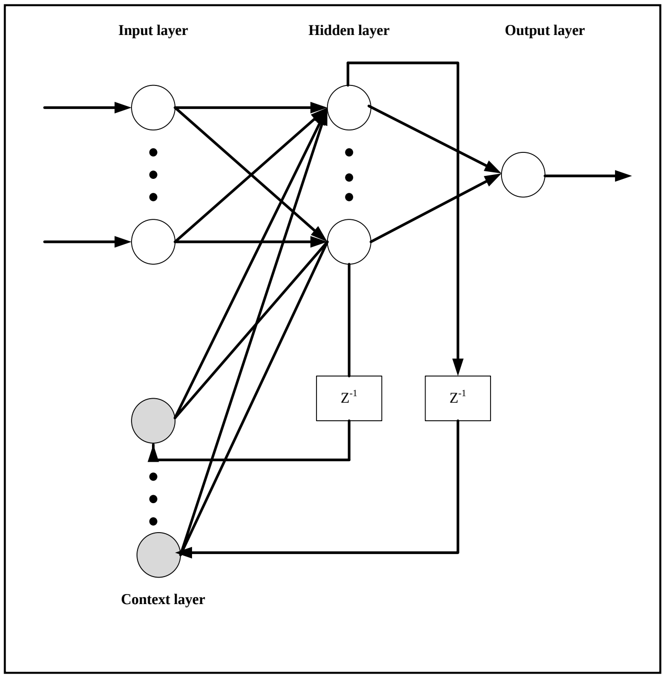


Fig 3. Structure of Elman Neural Network

2.4 Performance indices

The models in this study were evaluated using three performance metrics. These include coefficient of correlation (COC), coefficient of determination (COD) and root mean square error (RMSE). The performances of the forecasting models for training and testing dataset were determined using the following criteria:

2.4.1 Coefficient of Correlation

Coefficient of correlation is regarded as a statistical measure of the strength of an association or degree of a linear relationship that exists between two different variables. The values of correlation coefficients start from -1 to +1. It is expressed as:

$$COC = \frac{\sum_{i=1}^{n}(O_i - \bar{O})(P - \bar{P})}{\sqrt{\sum_{i=1}^{n}(O - \bar{O})^2 \sum_{i=1}^{n}(P_i - \bar{P})^2}} \tag{7}$$

2.4.2 Coefficient of Determination (COD)

Coefficient of determination is a performance index that shows how close the predicted values are closed to the fitted line or curve. It is expressed as:

$$COD = \left(\frac{\sum_{i=1}^{n}(O_i - \bar{O})(P - \bar{P})}{\sqrt{\sum_{i=1}^{n}(O - \bar{O})^2 \sum_{i=1}^{n}(P_i - \bar{P})^2}}\right)^2 \tag{8}$$

The values for coefficient of determination range from 0 to 1, with indicating perfect forecasting ability.

2.4.3 Root Mean Square Error (RSME)

RMSE shows the deviation between the predicted and observed water demand values. It is expressed as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_i - P_i)^2} \tag{9}$$

RMSE is always greater 0.

where O_i and P_i are observed and estimated water consumption respectively, $\bar{O}$ and $\bar{P}$ are means of the observed and estimated water consumption, respectively, and n is the number of data points [1], [4].

3 RESULTS AND DISCUSSIONS

3.1 Simulation Results and Analysis

The study involved training and testing of three variants of artificial neural networks using the simulation parameters in Table 3.

Table 3: Simulation parameters

Parameters	**Values**
Number of hidden layer	1
Number of neurons in hidden layer	5
Error goal	0.1
Activation function	Tangent sigmoid

Firstly, the simulation study of the trained neural network models based on a single input variable from the testing data was performed as shown in Table 4.

Table 4: General structure of forecasting models based on a single input variable

Model	Input Structure	Output
M1	WC(t-1)	WC(t)
M2	TP(t)	WC(t)
M3	HD(t)	WC(t)
M4	PL(t)	WC(t)
M5	GG(t)	WC(t)
M6	IR(t)	WC(t)

A careful evaluation of Table 5, the models performed differently based on the three performance criteria. The highest value of RMSE among the three forecasting models is 1.0998 (in M2 of FFNN) and the lowest value of the RMSE is 0.4259 (in M1 of CFNN). Furthermore, the highest value of correlation coefficient (COC) and coefficient of determination (COD) are 0.9459 and 0.8947 respectively in M1 of CFNN. It can be deduced that the performance of CFNN models performs better than FFNN and ENN models according to the performance evaluation criteria obtained in Table 5.

Table 5: Comparison of performances of ANN forecasting models based on a single input variable

MDL	FFNN			CFNN			ELNN		
	coc	**cod**	**rmse**	**coc**	**cod**	**rmse**	**coc**	**cod**	**rmse**
M1	0.92	0.86	0.43	0.94	0.89	0.42	0.94	0.89	0.46
M2	0.30	0.09	1.09	0.38	0.14	0.98	0.26	0.06	1.04
M3	0.35	0.12	0.99	0.40	0.16	0.97	0.14	0.02	1.05
M4	0.88	0.78	0.53	0.87	0.76	0.55	0.87	0.76	0.56
M5	0.67	0.45	0.81	0.54	0.29	0.90	0.54	0.29	0.89
M6	0.46	0.21	0.94	0.42	0.18	0.96	0.30	0.09	1.02

From this comparative analysis, in model M1, it was observed that the past monthly data (*WC(t-1)*) to be highly correlated to the water consumption (*WC(t)*), while in models M2 to M6, the input variables showed moderate and low correlations with water consumption. Thus, the following variables: temperature (*TP(t)*); humidity (*HD(t)*); inflation rate (*IR(t)*); population (*PL(t)*) and GDP growth rate (*GG(t)*) were used to determine the performance of the forecasting models. From Table 5, the model with best fit results among the five forecasting models is M4 based on the performance indices used in this study.

The second simulation study was based on twenty (20) models with multiple input variables to forecast the water consumption using different combinations of the single input variables. The structures and configurations of these models are shown in Table 6. The models were trained and tested by the dataset and the performances of the second simulation study are presented in Figs 4, 5 and 6.

Table 6: Model structures of forecasting models using multiple input variables

MDL	FFNN			CFNN			ELNN		
	coc	**cod**	**rmse**	**coc**	**cod**	**rmse**	**coc**	**cod**	**rmse**
M7	0.54	0.29	0.96	0.48	0.23	0.93	0.29	0.08	1.02
M8	0.87	0.75	0.56	0.94	0.88	0.42	0.93	0.88	0.45
M9	0.65	0.43	0.82	0.81	0.66	0.63	0.68	0.46	0.81
M10	0.57	0.33	0.91	0.71	0.50	0.76	0.43	0.18	0.99
M11	0.83	0.69	0.67	0.88	0.78	0.51	0.88	0.78	0.64
M12	0.63	0.40	0.82	0.77	0.60	0.68	0.53	0.29	0.89
M13	0.62	0.38	0.84	0.55	0.30	0.93	0.30	0.09	1.01
M14	0.92	0.85	0.44	0.93	0.87	0.44	0.87	0.76	0.56
M15	0.88	0.78	0.54	0.92	0.85	0.48	0.87	0.76	0.56
M16	0.66	0.44	0.80	0.58	0.33	0.86	0.54	0.29	0.91
M17	0.94	0.89	0.47	0.93	0.87	0.42	0.94	0.88	0.46
M18	0.77	0.59	0.68	0.91	0.83	0.48	0.68	0.46	0.81
M19	0.71	0.50	0.79	0.70	0.49	0.76	0.43	0.18	0.97
M20	0.93	0.86	0.46	0.87	0.76	0.56	0.88	0.77	0.56
M21	0.58	0.33	0.92	0.84	0.71	0.60	0.52	0.27	0.92
M22	0.89	0.80	0.50	0.91	0.83	0.49	0.87	0.77	0.57
M23	0.94	0.88	0.40	0.95	0.90	0.39	0.93	0.87	0.46
M24	0.91	0.83	0.50	0.95	0.91	0.38	0.94	0.89	0.48
M25	0.82	0.68	0.62	0.84	0.70	0.62	0.87	0.77	0.58
M26	0.91	0.82	0.48	0.95	0.90	0.39	0.93	0.87	0.47

From the results of the models in Table 6, it is observed that the performances of CFNN models were better than other two models. The values of coefficient of determination for M24 models are higher than those of other nineteen (19) models. The correlation coefficients values of M24 models are higher than the other models. In addition, RMSE values of M24 models are found to be smallest among the models tested.

Based on the performance metrics used in the study, it was found that the M24 models consisting of temperature, humidity, population and inflation rate demonstrated the best abilities to predict monthly water consumption of Oman. It was observed that these four variables have significant effect on the performance of three neural network models (M24 FFNN, M24 CFNN and M24 ENN) based on the evaluation indices of the study.

In order to determine or identify the best model among three variants of artificial neural networks (multiple variables) considered in this study (M24 FFNN, M24 CFNN and M24 ELNN) and the neural network with singe input (M4 CFNN), their performances were compared with M4 CFNN as shown in Table 7.

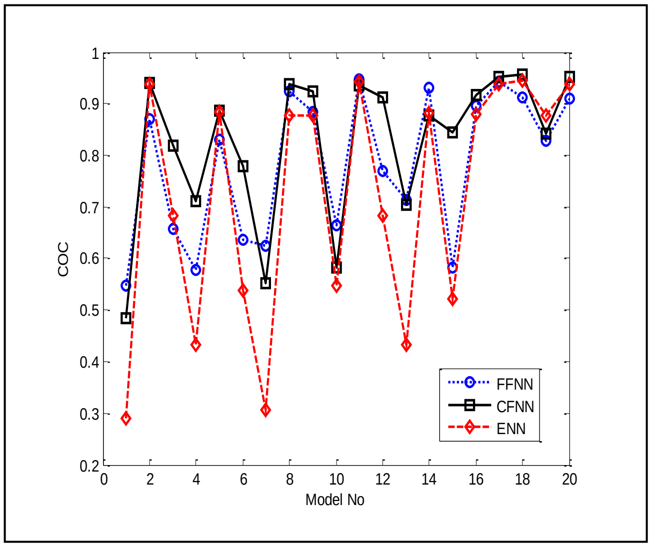


Fig. 4 Comparison of the performances of neural network models based on Correlation Coefficient (COC) metric

International Journal of Academic Engineering Research (IJAER)
ISSN: 2643-9085
Vol. 7 Issue 3, March - 2023, Pages: 1-9

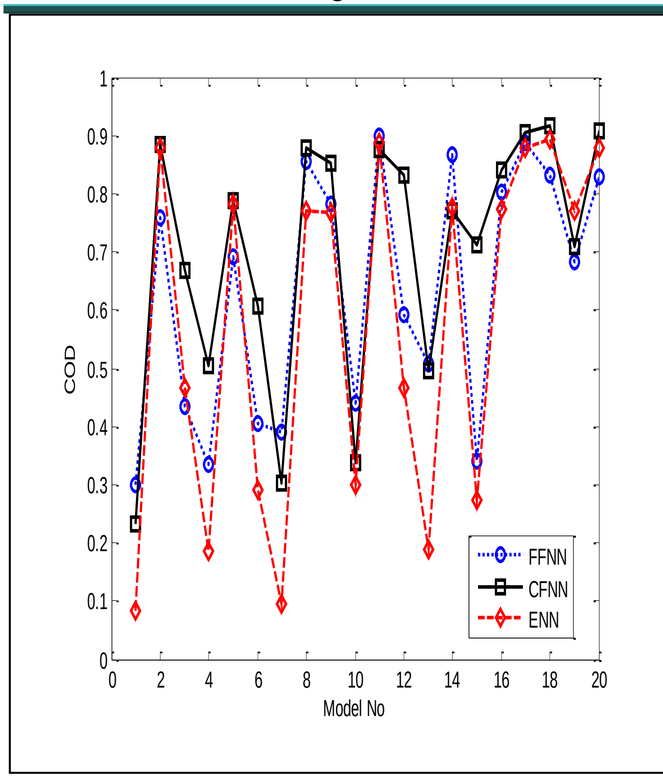


Fig. 5 Comparison of the performances of neural network models based on coefficient of determination (COD) metric

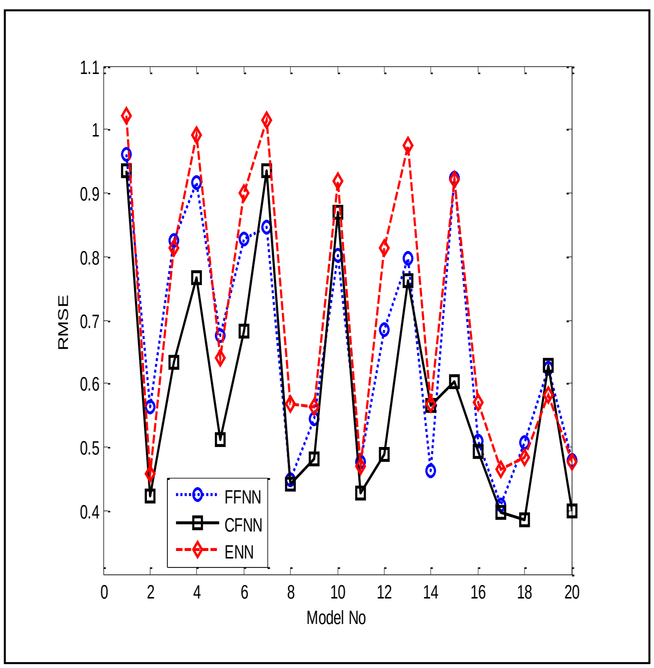
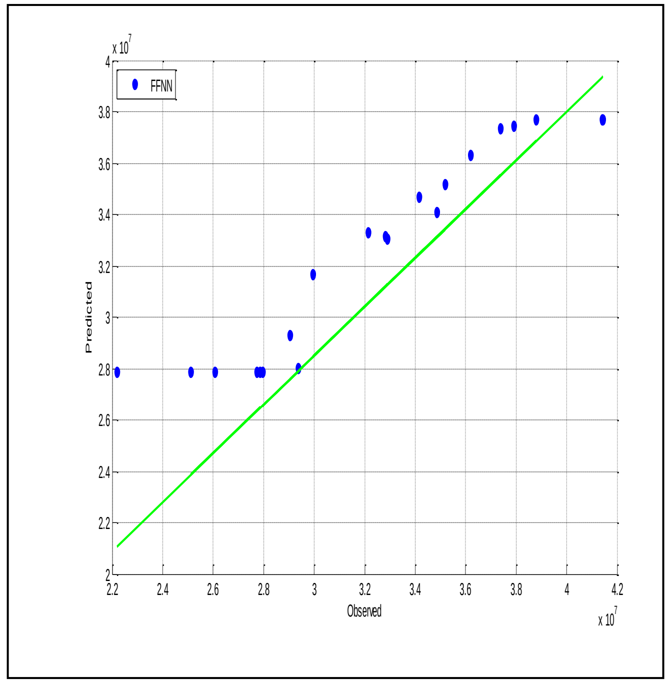


Fig. 6 Comparison of the performances of neural network models based on RMSE metric

A careful examination of Table 7 and Figures 7(a) – (d) showed that the performance of M24 CFNN having multi-input variables was the best among the four models considered in the third simulation study. M24 CFNN recorded the highest values of COC and COD.



(a) Result of M24 – FFNN performance

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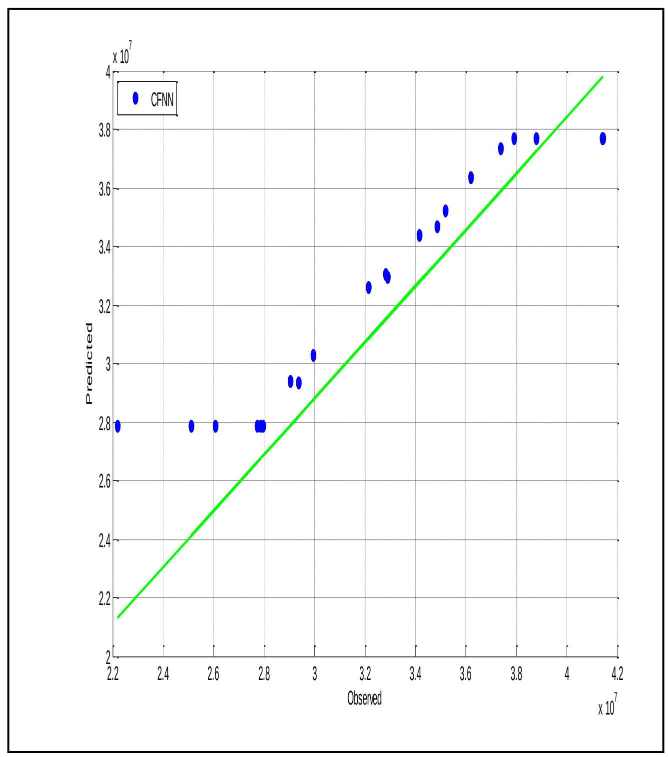
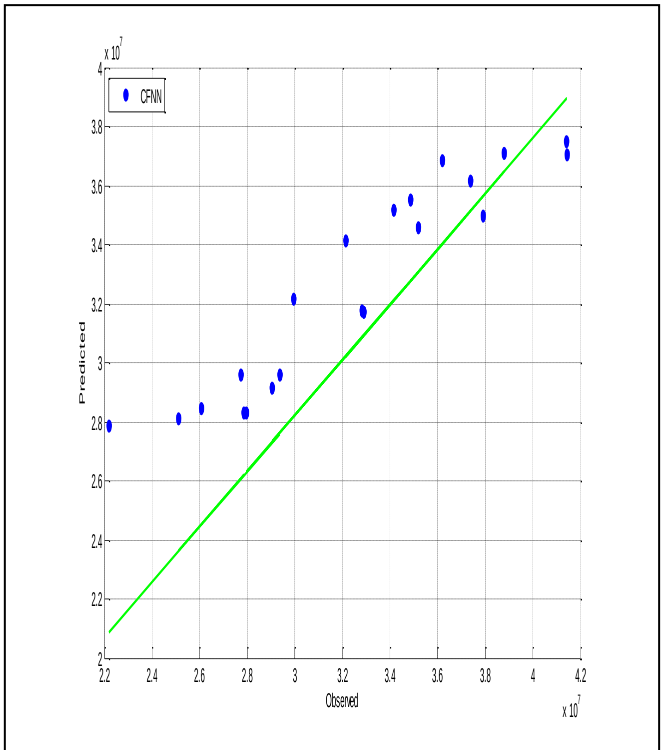
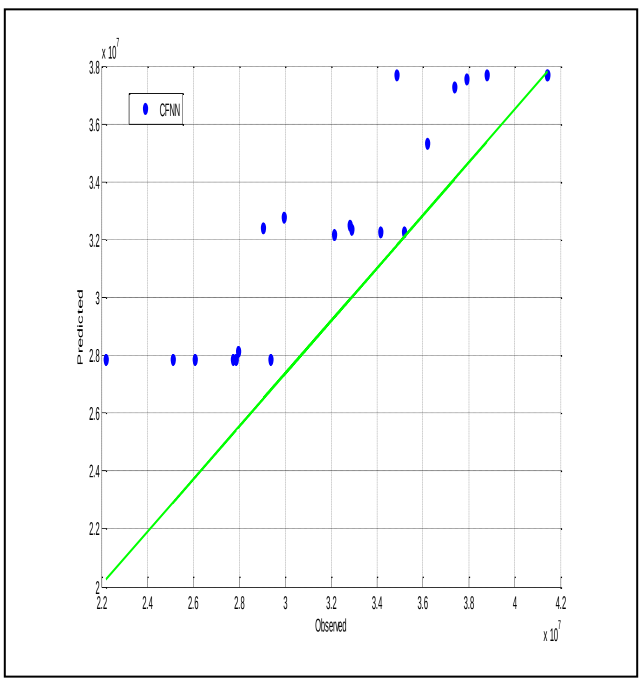


(b) Result of M24 – CFNN performance



(c) *Result of M24 ELNN performance*



(d) *Result of M4 CFNN performance*

Fig. 7 Comparing the results of M24-FFNN, CFNN, ELNN and M4 CFNN performance

4 CONCLUSION

Water demand management has been identified an means of providing information to the managers in order to manage peak demands or perturbation when they occur. The study was performed to compare the performance of feed forward, cascade forward and Elman neutral networks to analyse water demand modeling in short-term water demand forecasting using historical data of Oman. It was inferred from the study that cascade forward neural network with multiple inputs performed better than Elman and feed forward neural networks. Temperature, humidity, inflation rate and population were found to have significant effect on water demand in Oman.

The limitation of this study is that some climatic and socio-economic variables were applied to develop the water demand forecast models. It does not show the variation in seasons and consumption in different parts of the Country including high and low water users. These variations are vital to determine the future ware demand and conservation. Therefore, further studies that may integrate proxies that will account for spatial and temporal patterns of water usage, effect of policy interventions, climate change and consumers' behavior in water demand estimation should be carried out.

Future studies may also cover development of new measures to interpret the results of the models and improve the causal relationship between the water demand and the socio-economic and demographic variables involved in the development of forecast models.

ACKNOWLEDGMENT

Special thanks to the Management of National Board for Technical Education, Kaduna, Nigeria for supporting this study.

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