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REVIEW ON SHORT-TERM URBAN WATER DEMAND FORECASTING

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ABSTRACT

Water demand forecasting has become an essential component in effective water resource planning and management. It provides valuable triggers in determining the time and the capacity for new water resource development. Therefore, there is an increased need for water demand forecasting, because it can provide a simulated view of the future, and contribute to identifying a suitable management alternative in balancing water supply and demand. It will be a great challenge to meet the increased demand for water due to increasing population, economic growth and technological changes. with development, the water demand is increasing both in urban and rural areas. This may increase stress and disputes over sharing of limited water resources. The rapid growth of the population and its growing needs have meant that the per capita availability of fresh water has declined sharply. Forecasting is a planning tool that helps management to deal with the uncertainty of the future. This study presents a literature view of water demand forecasting methods and models, for proper planning and implementation of urban water demand management schemes. It was found that Artificial Neural Network and hybrid model perform better for short-term water demand forecasting.

Keywords: Water demand, water demand forecasting, artificial neural network, hybrid model.

2. GENERAL MODEL

There are various models and methods are available for urban water demand forecasting and these can be either qualitative or quantitative.. The qualitative forecasting techniques are subjective and they are used to forecast future data based on the opinions and judgments of consumers and experts. So, they are suitable when past data are not available. On the other hand, quantitative forecasting models are suitable when past data are available because they are used to forecast future data based on past data (Yanyan, 2012). Quantitative forecasting will be discussed in the study.

2.1 Regression Analysis Method

Regression analysis is the process of constructing a mathematical model that can be used to predict one variable by another variable or variables. The regression model specifies the relation of a dependent variable (Y) to a function combination of independent variables (X) and unknown parameter $Y \approx f(X, \beta)$. Commonly, regression analysis is used for prediction and forecasting. It is also known as curve fitting or line fitting because it can be used in fitting a curve or line through a scatter plot of paired observations between two variables. So, the regression line shown in Figure 1 is usually determined quantitatively by the best fit (the differences in the distances of data points or observations from the curve or line are minimized).

There are two different types of regression analysis simple linear regression and multiple linear regression (Mohamed and Al-Mualla, 2010). Linear regression technique uses a line to predict the outcome; one independent variable is plotted on the x-axis and another dependent variable is plotted on the y-axis. The multiple regression technique uses two or more independent variables to predict the outcome. Additionally, the formula for each type of regression is given by Investopedia (2015) as follows:

- Linear Regression: Y = a + b X + u (Eq. 1)

- Multiple Regression: Y = a + b1 X1 + b2 X2 + b3 X3 + ... + bt Xt + u (Eq. 2)

Where:

Y= the variable that we are trying to predict

X= the variable that we are using to predict Y

a= the intercept of a regression line

b= the slope of a regression line

u= the regression residual.

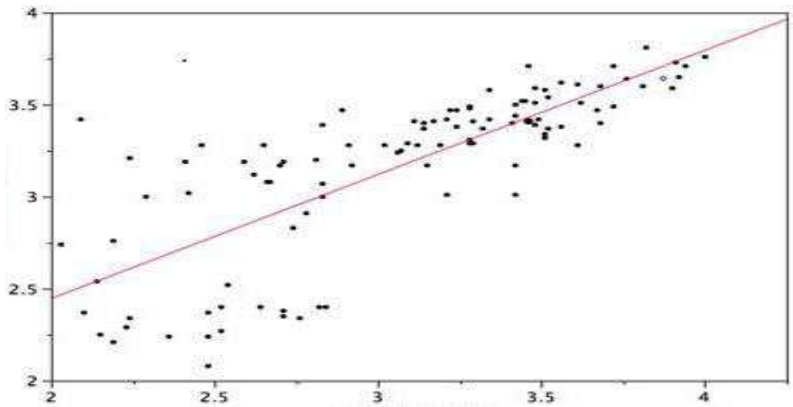

Figure1: Linear Regression (Lane, 2006)

2.2 Time Series Analysis Method

A time series is a sequence of observations on a variable measured over successive periods. The measurements may be taken every hour, day, week, month, or year, or at any other regular interval. There is no minimum or maximum amount of time to be included. Donkor et al. (2012) mentioned that a time series model forecasts future value based on past observations. This class of models does not account for the effect of exogenous variables such as weather or price It relies on the assumption that past trends will be repeated in the future. Time series analysis has two classes of components which are trend and seasonality. Trends are consecutive increases or decreases in a measurement over time. A trend could last several, days, months or years. Seasonality is measured over a specific period (Zhang, 2001)

However, time series models are the most accurate alternative when weather changes are likely to occur in the underlying determinants of water demands. Exponential smoothing, autoregressive (AR), moving average (MA), autoregressive-moving average (ARMA), autoregressive integrated moving average (ARIMA) and seasonal ARIMA (SARIMA) are examples of time series forecasting models (Donkor et al., 2012)

2.3 Artificial Neural Network Technique

The ANN was constructed to model and imitate the intelligence of the human brain in a machine (Ghalehkhondabi et al., 2017) Although the development of ANNs was mainly biologically motivated, afterward, they have been applied in many different areas, especially for forecasting and classification purposes (Hill 1994, Zhang 2008). ANN model learns from experience and then provides generalized results based on their known previous knowledge. Three-layer feed-forward ANN is shown in figure 2.

Zhang et al. mentioned the salient features of ANNs, which make them quite a favorite for forecasting. First, ANNs are data-driven and self-adaptive in nature. They learn from examples and capture functional relationships among the data even if the relationships are unknown or hard to describe. Second, ANNs are non-linear, which makes them more practical and accurate in modeling complex data patterns. Finally, as suggested by Hornik and Stinchcombe ANNs are universal functional approximators. It has been shown that a network can approximate any continuous function to any desired accuracy. ANNs use parallel processing of the information from the data to approximate a large class of functions with a high degree of accuracy. Further, they can deal with situations, where the input data are erroneous, incomplete or fuzzy (Cheng and Titteringto, 1994).

The ANN model is characterized by three layers, input, hidden and output layer, connected by acyclic links. There may be more than one hidden layer. The nodes in various layers are known as processing elements. The three-layer feed-forward architecture of ANN models can be diagrammatically depicted as below:

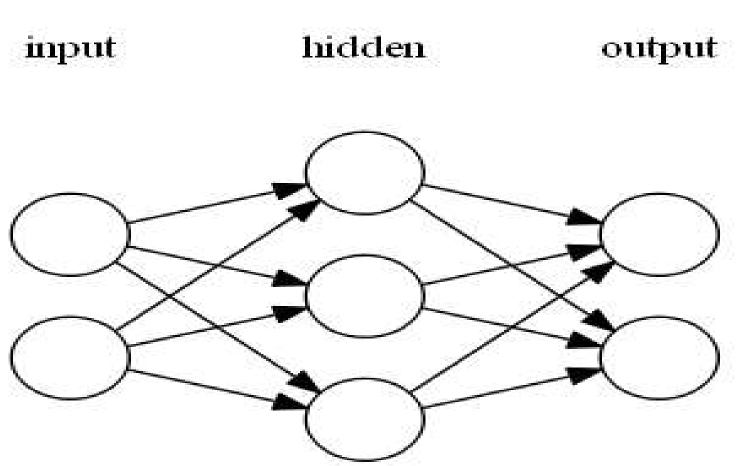

Figure 2 Three-layer feed-forward ANN architecture (Ghiassi and Saidane, 2005)

2.4 Support Vector Machines

SVM is a learning technique with accompanying learning algorithms that recognize patterns and analyze data (Cortes and Vapnik, 1995). The basic idea of the SVM model is to represent a set of input data as points in space, mapped so that the separate groups are divided by a clear gap. Group separation of data points is shown in figure 3. A line is created which separates the classes (Suykens and Vandewalle, 2000). In this method, an optimal separating hyperplane is constructed, after nonlinearly mapping the input space into a higher dimensional feature space. SVM-based model selection certainly manages to improve the forecasting results in terms of both errors and bias. (Villegas, 2018)

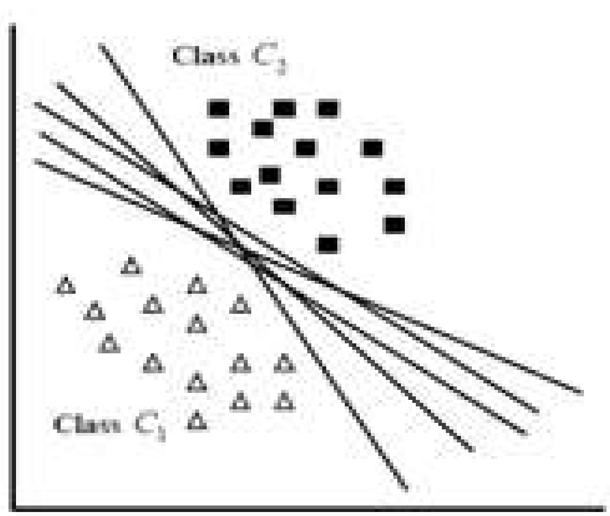

Figure 3: Hyperplane classify data (Jakkula, 2006)

2.5 Fuzzy Logic Method

Zadeh (1965) developed the concept of fuzzy logic. Klir and Yuan (1995) explained that a fuzzy logic method is non monotonic logic. It is a suitable method for human reasoning so, it represents some form of incomplete or uncertain data. Also, fuzzy logic is planned to obtain the best possible decision given the input by considering all available information and it can be indicated with degrees of truthfulness and falsehood. Moreover, fuzzy logic can be used in other artificial intelligence applications to produce fuzzy systems that can adapt and learn.

2.6 Hybrid approaches

These approaches combine two or more different approaches in order to overcome the drawbacks of the original technique (Jain and Kumar, 2007). Combining multiple models can be an effective way to improve forecasting performance (Zhang, 2007). Genetic algorithms or other evolutionary algorithms can be applied in combination with neural networks. Such an approach can be called as a hybrid approach.

3. LITERATURE REVIEW

This section presents a comprehensive study and review of various research papers in the area of water demand prediction using various techniques and methods.

Lertpalangsunti et al. (1999) present the Intelligent Forecasters Construction Set (IFCS) toolkit for daily water demand prediction for the City of Regina, Canada. The IFCS supports the four intelligent techniques of fuzzy logic, neural networks, rule-based and case-based reasoning; it also supports online prediction. The parameters day of the week, temperature, humidity, rainfall, snowfall and wind speed are used for the development of a model. Multiple ANN approach outperformed case based reasoning (CBR) and linear regression LR analysis. Mean Absolute Percentage Error (MAPE) is used for performance evaluation.

Jain et al. (2001) compare the conventional method (regression & time series) with ANN to forecast water demand at IIT Kanpur. In the study data on weekly water demand is taken from the IIT Kanpur campus and total weekly rainfall, and average maximum air temperature from the city of Kanpur. The complex ANN model outperforms the other conventional models. It is also investigated that the occurrence of rainfall is a more significant explanatory variable than the amount of rainfall in the short term water demand process.

Jain and Ormbsbee (2002) compared the conventional method of time series & regression analysis to relatively new artificial intelligence (AI) techniques such as expert systems and ANN. Daily water demand, daily maximum air temperature and daily total rainfall data taken from Lexington Ky, United States were used to investigate short term water demand forecasting. In the study, the performance of each model was evaluated using two standard statistical parameters average absolute relative (AARA) error and Threshold Statistic (TSx). AI models outperformed conventional models.

Zhang G. Peter (2003) presented a hybrid methodology that combines both linear ARIMA and non-linear ANN models to take advantage of the unique strength of ARIMA and ANN. Three well-known data sets Wolf's sunspot data, the Canadian lynx data, and the British pound/US dollar exchange rate data are used in the study to forecast one, six and twelve month water demand. Experimental results indicate that the combined model can be an effective way to improve forecasting accuracy achieved by either of the models used separately. The hybrid model outperforms ARIMA and ANN models in terms of MSE and MAD.

Bougadis et al. (2005) utilize data from the city of Ottawa, Ontario, Canada to present a paper on short term urban water demand forecasting. In this paper ANN, regression and time-series models have been developed and compared. The feedforward neural network (FNN) consistently outperformed the regression and time-series model. It has been found that water demand on a weekly basis is more significantly correlated with the rainfall amount than the occurrence of rainfall. It is also observed that the ANN technique substantially outperformed regression and time-series methods in terms of accuracy of forecasting.

Adamowski Franklin Jan (2008) compares multiple linear regression, time series analysis, and artificial neural networks for peak daily summer water demand. For The analysis of the study, 10 years of peak daily water demand data were taken from Ottawa, Canada. The meteorological variables maximum daily temperature and daily rainfall for the summer months of May to August were used. ANN models outperformed the regression and time series models, recording the lowest AARE and Max ARE statistics. While the highest R^2 value is recorded in training and testing. It is also clear that the regression models outperformed the time series models.

Ghiassi et al (2008) compared the performance of the dynamic artificial neural network (DANN), ARIMA and feed forward back propagation neural network (FFBP). The inclusion of weather information can improve the accuracy. Data has been taken from California, USA. The paper addresses a comprehensive approach to forecast hourly, daily, weekly and monthly water demand. DAN2 models can provide excellent fit and forecasts without dependence upon the explicit inclusion of weather factors. The monthly, weekly, and daily models produce forecasting accuracies above 99%, and the hourly models above 97%. DAN2 outperformed both the ARIMA and ANN methods across all time horizons

Alhumoud M. Jasem (2008) applied the time series (ARIMA) method for forecasting long term water consumption in Kuwait. In this paper, correlation is used to assess the relationship between water consumption and its determinants and provide a descriptive model of annual water consumption.

Adamowski and Karapataki (2010) forecast short term peak urban water demand in Nicosia city of Cyprus. In this research multilayer perceptron with a different learning algorithm Levenberg-Marquardt (LM), resilient back-propagation (RP) and Conjugate gradient Powell-Beale (CGB) was developed and compared with a conventional method multiple linear regression (MLR). The maximum weekly temperature and total weekly rainfall were considered the most effective variables and six years' worth of data was applied in the model. It has been noticed that the LM ANN method was found to provide a more accurate prediction of peak weekly water demand than the other two types of ANNs and multiple linear regression. The LM algorithm is the fastest method for training moderate-sized feedforward neural networks. The coefficient of determination (R2), root-mean-square error (RMSE), average absolute relative error (AARE), and the maximum absolute relative error (Max ARE) are used for the evaluation of the performance of model.

Harrera et al (2010) compare four different models for hourly water demand forecast. In his paper data analysis is taken from a city in Spain for the comparison of four models ANN, Projection pursuit regression (PPR), Multivariate adaptive regression splines (MARS), random forest (RF) and SVR. Four parameters are introduced for the performance of models. The results of the comparison have identified SVR as the most accurate model closely followed by MAES, PPR and RF. The performance evaluation statistics used in the article are RMSE, MAE, Nash-Sutcliffe efficiency and modification of Nash-Sutcliffe.

Lee et al (2010) presented a paper on forecasting long term water demand in the City of Phoenix, Arizona. Co-kriging, Kriging with measurement error and Bayesian maximum entropy (BME) methods are compared. Water estimates are derived using the first and second-order statistical moments between a dependent variable, water use and an independent variable, population density. The independent variable is projected at future points, and remains uncertain. BME outperformed other models in terms of mean square error (MSE) and determined the regression relationship between water demand and population density.

Polebitski and Palmer (2010) presented a paper on forecasting annual residential water demand in the city of Seattle, Washington. Regression based models are developed and compared. It has been determined that lot size, density, and building size influence water demand patterns and should be included as variables in water demand models. RMSE is used to evaluate the performance of models.

Nasseri et al. (2011) present a hybrid model which combines extended kalman filter (EKF) and genetic programming (GP) for forecasting monthly water demand in Tehran. EKFGP model outperforms traditional, regression and time series methods. The results can help decision makers to reduce the risks of online water demand forecasting and optimal operation of an urban water system. Two important statistical criteria, Normal Mean Square Error (NMSE) and determination coefficient (R^2) are used to evaluate the performance of the model.

Odan and Reis (2012) addressed the best fit model using hourly consumption data from the water supply system of Araraquara, Sao Paulo, Brazil. The ANN multilayer perceptron with a back-propagation training algorithm (MLP-BP), the DAN2, and the two hybrid neural networks ANN-H and DAN2-H were used for the research. The tested forecasting models were evaluated using the Mean Absolute Error (MAE) and Pearson Correlation

Coefficient (r) criteria. It was found that the best forecasting model DAN2-H 2, for the first hour prediction and DAN2-H 4 for the 24 h prediction.

Yasar et al. (2012) present a paper to determine the most suitable independent variables for forecasting the monthly water demand in Adana city Turkey. The stepwise multiple nonlinear regression method was used to develop the model. To get a successful simulation, first, all independent variables were added to the single regression model. Then, the method of stepwise multiple regression was applied for the selection of the best regression equation. It has been found that monthly water demand is directly related to the total number of subscribers and atmospheric temperature. MAPE and R is used for the performance evaluation of the model

Yuefeng et al. (2012) address the number of hidden layers and neurons in each layer can directly impact the performance of ANN. A certain basin in China is taken as a case study. The backpropagation (BP) neural network is presented in this paper for water demand forecasting. Focusing on this issue an empirical formula and trial and error method are used to find the number of neurons in the middle layer for water demand forecasting.

Al-Zahrani and Abo-Monasar (2015) presented a prediction of future daily water demand for Al-Khobar city in the Kingdom of Saudi Arabia. The combined technique of general regression neural network (GRNN) and time series models was constructed based on the available daily water consumption and climatic data. The developed model is compared with the GRNN and TS model alone. Results indicate that combining time series models with ANN models will give better prediction compared to the use of ANNs or time series models alone. The criterion used for the evaluation of performance of model is R^2 and MAPE. The results show that temperature is the most important meteorological predictor in training the neural networks. Humidity, wind speed and rainfall occurrence are also important predictors, but they cannot be used alone without temperature.

Tiwari and Adamowski (2015) forecast medium term urban water demand with limited data using hybrid wavelet-bootstrap-artificial neural network (WBANN) modeling approach. The data sample for observation is taken from Calgary, Canada. Wavelet transforms and bootstrap combined to form a wavelet-bootstrap-ANN. (WBANN) model has the potential to increase accuracy and reliability. The bootstrap is a data-driven simulation method that uses intensive resampling with replacement to reduce uncertainties. The technique is based on resampling with replacement of the available dataset and training an individual network on each resampled instance of the original dataset. WBANN was found to perform better in terms of R2, RMSE, Pdv and MAE performance indices than ANN, WANN and BANN

Mouatadid and Adamowski (2017) present an approach using extreme learning machine algorithms for short term urban water demand forecasting. Data used in the study were obtained from the city of Montreal, Canada between 1999 to 2010. The study investigated the ability of data driven model to forecast accurate and reliable 1 and 3 day lead time. ANN, SVR, MLR and ELM were developed and compared. It has been observed that ELM model outperforms other models and is independent of lead time. The performance is quantified by R^2 and RMSE statistic parameters.

Perea et al (2018) presented a paper on short term daily irrigation water demand forecast when data availability is limited. The hybrid model has been developed by coupling artificial neural network (ANN) and genetic algorithms (GA). In this study, historical data from a district of southern spain is taken. GAs is implemented in the ANN optimization under bayesian framework. It has been noticed that two subsets training and testing sets are used rather than three subsets training, validation and testing sets. The developed model improved the prediction accuracy by between 3% and 11 % with respect to previous work. The performance of the model is evaluated by standard error prediction and R^2

Zubaidi et al (2018) present an approach to forecast water in Melbourne city of Australia. In this paper, monthly water demand is predicted by combining singular spectrum analysis with a neural network. Historical monthly water consumption data from 2006-2015 was used. In the approach, a hybrid particle swarm optimization algorithm and an artificial neural network (PSO-ANN) input with a climatic factor are taken. The PSO-ANN algorithm was shown to be a reliable prediction model, outperforming the hybrid Backtracking Search Algorithm BSA-ANN in terms of fitness function (RMSE).

4. SUMMARY

The summary of the literature survey is shown in table 1.

Table 1: Summary of Literature Survey

	REF	Technique	Locatilmon	Determinants	Output/Observation	Performance Metric
Regression-Based Methods						
1.	Lee et al. (2010)	Used Co-kriging, Kriging with measurement error Bayesian maximum entropy (BME) to estimate the regression relationship between water demand and population density.	Phoenix, Arizona , USA	Population density	Long term annual forecast Improved forecasting accuracy up to 43.9% over other space–time mapping	Mean square error (MSE) is used to evaluate the accuracy of model.
2.	Polebitski and Palmer (2010)	Developed a regression-based water demand models capable of forecasting single-family residential water demands	Seattle, Washington, USA	Density, building size, lot size, household size, income, price, temp, rain	Medium term: monthly water demand	Root mean square error (RMSE) is used to compare the performance of the models
Time Series Based Methods						
3.	Alhumoud M. Jasem (2008)	ARIMA Method	Kuwait	total annual residential water consumption	1. Long term annual forecast 2. Correlation between socio economic traits like residence type, house size, no. of cars etc) and there water consumption. 3. Assist the government to subside water consumption.	---
4.	Yasar et al. (2012)	Stepwise multiple nonlinear regression method	Adana, Turkey	Average monthly water bill, total subscribership , atmospheric temperature, relative	1. Forecast monthly water demand 2. Monthly water demand is directly related to the total number of subscribers and atmospheric	The mean absolute percentage error (MAPE) and correlation coefficient (*R*) were used for the

				humidity, rainfall, global solar radiation, sunshine duration, wind speed and atmospheric pressure	temperature.	performance evaluation.
Artificial Neural Network Based Methods						
5.	Lertpalang sunti et al. (1999)	Multiple ANN, case based reasoning (CBR) and linear regression (LR)	Regina, Canada	Day of the week, temperature, humidity, rainfall, snowfall and wind speed	Short term daily water forecasting	mean absolute percentage error (MAPE)
6.	Mouatadid and Adamowsk i. (2017)	Extreme Learning Machine,ANN, SVR and MLR	Montreal, Canada	Average daily water demand, maximum temperature, total precipitation and occurrence of precipitation recorded at one day ago,and 3-day ago	1. Short term: 1 day, & 3-day lead time water demand forecasting 2. ELM outperformed other data driven methods in terms of learning speed. ELM model forecast accurate and reliable 1&3 day lead time water demand forecasting.	RMSE and coefficient of determination (R^2) are used for performance evaluation of the model.
7.	Bougadis et al. (2005)	ANN, regression and time-series models have been developed and compared.	Ottawa, Ontario, Canada	Week(peak water demand, average maximum temperature and total rainfall	1. Short term weekly water demand forecasting 2. The ANN models consistently outperformed the regression and time-series model in terms of accuracy. 3. The amount of rainfall is more significant than the rainfall occurrence	R^2, average absolute relative error (AARE), and the maximum absolute relative error (Max ARE) are used for the evaluation of performance of model
8.	Adamowsk i and Karapataki (2010)	Three different types of multilayer perceptron model and multiple linear regression model (MLR) were developed	Nicosia , Cyprus	Peak water-demand , maximum weekly temperature and total weekly rainfall	1. Short term peak weekly water demand forecasting. 2. Neural network using different learning algorithm Levenberg-Marquardt(LM), resilient back-	Coefficient of determination (R^2), root-mean-square error (RMSE), average absolute relative error (AARE), and the maximum absolute relative

					propagation (RB) and conjugate gradient Powell-Beale (CGP) were developed and compared with MLR. 3. LM ANN found to provide a more accurate prediction than the other two types of ANNs and multiple linear regressions. 4. The peak weekly water demand is better correlated with the rainfall occurrence rather than the amount of rainfall itself. 5. LM ANN found to be faster method for training moderate sized FFN.	error (Max ARE) are used for the evaluation of performance of model.
9.	Sun et al. (2012)	ANN	Certain basin in China	Water demand, temperature, pressure	1. Number of neurons in the mid-layer is calculated using the empirical equation and trial and error methods. 2. The results of the model will support in decision making area of water resource planning and management	Statistical parameters ARE and Max. RE is used for the evaluation of the performance of model.
10	Ghiassi et al. (2008)	Dynamic Artificial Neural Network, BP ANN and ARIMA Model	California, USA	Water volume data and weather input	1. Short term: Hourly, daily, weekly and monthly water demand. 2. DAN2 outperformed both ARIMA and ANN models with 99% and 97% respectively accuracy for daily and hourly forecasting.	All models are evaluated with the mean absolute percent error (MAPE) statistic.
11.	Jain and Ormsbee (2002)	time series, regression method, expert system and ANN.	Lexington *Kentucky, US*	Water demand, temperature & total rainfall	1. Short term: daily water demand forecasting. 2. ANN model outperformed the	Statistical parameters used to test the performance of the model are

					expert system followed by the time series and regression model.	average absolute relative error (AARE) and threshold static (TS).
12.	Adamowski F. Jan (2008)	ANN, time series and regression	Ottawa, Canada	Maximum daily air temperature and daily rainfall	1. Short term: peak daily summer water demand forecasting. 2. ANN model outperformed regression followed by time series	2. Statistical parameters used for evaluation of performance are AARE, Max ARE, R^2
13.	Jain et al. (2001)	ANN, time series and regression model	IIT Kanpur, India	Weekly rainfall and maximum air temperature	1. Short term: weekly water demand forecasting. 2. Occurrence of rainfall is more significant variable then amount of rainfall.	3. Average absolute relative error (AARE), threshold statistic (TS_x), Max ARE, coefficient of correlation (R^2) is used to test the performance of model.
Support Vector Machine Based Methods						
14.	Harrera et al. (2010)	Four ANN model, project pursuit regression (PPR), Multivariate adaptive regression splines (MARS), random forest (RF) and SVR	City of Spain	Water consumption, temperature, wind velocity, rainfall, atmospheric pressure, mean sea level pressure	1. Short term: hourly water demand forecasting. 2. Besides the learning algorithm, a number of hidden layers and neurons in each layer can directly impact the performance of ANN. 3. SVR is the most accurate followed by MARS,PPR&RF	Performance metrics used in the study are RMSE, MAE, Nash- Sutcliffe (E) and modified Nash- Sutcliffe (D).
Hybrid Approach Based Methods						
15.	Tiwari and Adamowski (2015)	Wavelet bootstrap artificial neural network (WBANN) ANN, bootstrap based artificial neural network (BANN) and wavelet based artificial neural network (WANN)	Calgary, Canada	Maximum temperature, total precipitation and water demand	1. Short term: weekly and monthly water demand forecasting 2. The inclusion of wavelet analysis in ANN improves the performance of model and the model will work effectively even with very short data length. 3. WBANN outperforms BANN, WANN and ANN in terms of uncertainty and accuracy.	The performance of models was evaluated using RMSE, R^2, mean absolute error (MAE) and peak percentage deviation (P_{dt}).

16.	Nasseri et al. (2011)	Hybrid model Extended Kalman filter and genetic programming (EKFGP), Regression and Time series model	Tehran	Previous lags of water demand	Medium term: monthly water demand forecasting. 2. EKFGP help decision makers to reduce their risk of online water demand forecasting and optimal operation of urban water system. 3. EKFGP outperforms traditional forecasting model	Statistical criteria normal mean square error (NMSE) and determination coefficient (R^2) is used to evaluate the accuracy.
17.	Zubaidi et al (2018)	Hybrid model particle swarm optimization algorithm and artificial neural network (PSO-ANN), backtracking search algorithm (BSA-ANN)	Melbourne (Australia)	Water consumption, temperature, solar radiation, vapour pressure and rainfall	Medium term: monthly water demand forecasting. 2. PSO-ANN outperform (BSA-ANN).	Performance matrices used for the evaluation of models are RMSE.
18.	Odan and Reis (2012)	MLP-BP, DAN2 and two hybrid neural networks ANN-H and DAN2-H	Araraquara, Sao Paulo, Brazil	Temperature and relative humidity	1. Short term: hourly water demand forecasting. 2. DAN2-H outperformed other model.	Performance evaluation statistics are MAE and Pearson (r).
19.	A- Zahrani and Abo-Monasar (2015)	Combination of general regression neural network (GRNN) combined with time series (TS), ANN and TS model.	AI-Khobar, Saudi Arabia	Temperature, humidity, wind speed and rainfall	1. Temperature is most important predictor Humidity, rainfall and wind speed cannot be used alone without temperature. 2. Join of GRNN and TS model outperform ANN and TS model.	4. The performance of models was assessed by MAPE and i of determination (R^2).
20	Perea et al. (2018)	Hybrid model combining ANN and genetic Algorithm (GA)	City of Spain	Water demand in the previous day, water demand in the two previous day, temperature, solar radiation	1. Short term: daily irrigation water demand forecasting. 2. Predict water demand with short data set.	1. The developed model improved accuracy between 3% and 11% with respect to previous work. 2. Performance evaluation criteria is standard error prediction (SEP) and R^2.

5. FORECAST PERFORMANCE MEASURE

The general approach to model selection is to consider competing forecasting models in a sequence of steps:

a. Divide the data set into an estimation period (training set) and a hold-out period (testing set).

b. Estimation period is used to model the demand;

c. Evaluate the accuracy of the models by comparing the forecasts values for the hold-out period.

d. Select the best model based on its performance as measured by any of the popular error measures.

In each of the forthcoming definitions, y_t is the actual value, f_t is the forecasted value,

$e_t = y_t - f_t$ is the forecast error (Absolute error) and *n* is the size of the test set. Also $\bar{y} = \frac{1}{n}\sum_{t=1}^{n} y_t$ is the test mean and $\sigma^2 = \frac{1}{n-1}\sum_{t=1}^{n}\left(y_t - \bar{y}\right)^2$ is the test variance.

5.1 The Mean Absolute Error (MAE)

The mean absolute error is defined as (Cao and Tay 2003, Donkr et al. 2012, Hamzacebi 2008 and Zhang, 2007)

MAE = $\frac{1}{n}\sum_{t=1}^{n}\left|e_t\right|$. Its properties are:

a. It measures the average absolute deviation of forecasted values from original ones.

b. It is also termed as the *Mean Absolute Deviation (MAD)*.

c. It shows the magnitude of overall error, occurred due to forecasting..

d. It does not provide any idea about the direction of errors.

e. For a good forecast, the obtained MAE should be as small as possible.

5.2 The Mean Absolute Percentage Error (MAPE)

This measure is given by (Cao and Tay 2003, Donkr et al. 2012 and Hamzacebi, 2008)

MAPE = $\frac{1}{n}\sum_{t=1}^{n}\left|\frac{e_t}{y_t}\right| \times 100$. Its important features are:

a. This measure represents the percentage of average absolute error occurred.

b. It is independent of the scale of measurement, but affected by data transformation.

c. It does not show the direction of error.

d. MAPE does not panelize extreme deviations.

5.3 The Mean Percentage Error (MPE)

It is defined as (Flaherty, 2000)

MPE = $\frac{1}{n}\sum_{t=1}^{n}\left(\frac{e_t}{y_t}\right) \times 100$.

The properties of MPE are:

a. MPE represents the percentage of average error occurred, while forecasting.

b. It has similar properties as MAPE, except,

c. It shows the direction of error occurred.

d. Opposite signed errors affect each other and cancel out.

e. Obtaining a value of MPE close to zero, we cannot conclude that the orresponding model performed very well.

f. It is desirable that for a good forecast the obtained MPE should be small.

5.4 The Mean Squared Error (MSE)

Mathematical definition of this measure (Hamzacebi, 2008 and Zhang, 2003)

$$\text{MSE} = \frac{1}{n}\sum_{t=1}^{n} e_t^2 .$$

Its properties are:

a. It is a measure of average squared deviation of forecasted values.

b. As here the opposite signed errors do not offset one another, MSE gives an overall idea of the error occurred during forecasting.

c. It panelizes extreme errors occurred while forecasting.

d. MSE emphasizes the fact that the total forecast error is in fact much affected by large individual errors, i.e. large errors are much expensive than small errors.

e. MSE does not provide any idea about the direction of overall error.

f. MSE is sensitive to the change of scale and data transformations.

5.5 The Root Mean Squared Error (RMSE)

Mathematically, (Donkor et al., 2012 and Zhang, 2007)

$$\text{RMSE} = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n} e_t^2}$$

a. RMSE is nothing but the square root of calculated MSE.

b. All the properties of MSE hold for RMSE as well.

5.6 The Normalized Mean Squared Error (NMSE)

This measure is defined as (Cao and Tay, 2003)

$$\text{NMSE} = \frac{MSE}{\sigma^2} = \frac{1}{\sigma^2 n}\sum_{t=1}^{n} e_t^2$$

Its features are:

a. NMSE normalizes the obtained MSE after dividing it by the test variance.

b. It is a balanced error measure and is very effective in judging forecast accuracy of a model.

c. The smaller the NMSE value, the better forecast.

d. Other properties of NMSE are same as those of MSE.

5.7 Average Absolute Relative Error (AARE)
Mathematically, (Bougadis et al., 2005 and Shcherbakov et al., 2013)

$$\text{AARE} = \text{Relative Error (RE)} = \frac{\textit{Absolute}\ \text{Error}}{\textit{Actual Error}} = \frac{e_t}{y_t}$$

$$\text{Absolute Relative Error (ARE)} = \left|\frac{e_t}{y_t}\right| \text{ and AARE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{e_t}{y_t}\right|$$

a. It is useful when we want to assess the error relative to the value of the exact quantity.

b. Smaller value of AARE denotes better performance of the model.

5.8 Maximum Absolute Relative Error (Max. ARE)
This measure is defined as (Bougadis et al., 2005).

Max ARE = Max. $\left|\frac{e_t}{y_t}\right|$ Its features are

a. Smaller its value, the better the performance of the model.

b. It measures the robustness of the model.

5.9 Correlation Coefficient
This measure is defined as (Yasar et al., 2012)

$$R = \frac{n\sum xy - \left(\sum x\right)\left(\sum y\right)}{\sqrt{n\left(\sum x^2\right) - \left(\sum x\right)^2}\sqrt{n\left(\sum y^2\right) - \left(\sum y\right)^2}}$$

Correlation coefficient formulas are used to find how strong a relationship is between data. The formulas return a value between -1 and 1, where:

a. 1 indicates a strong positive relationship.

b. -1 indicates a strong negative relationship.

c. A result of zero indicates no relationship at all.

5.10 Coefficient of Determination
This measure is defined as (Mouatadid et al., 2016).

R^2 = Square of Correlation Coefficient

a. It measures the degree of correlation among the observed and forecasted values

b. The higher the $R2$ value with 1 being the maximum value better is the performance of the model.

5.11 Threshold Statistic
This measure is defined, (Jain et al., 2001)

$$TS_x = \frac{Y_x}{n} \times 100\%$$

Its features are

a. The threshold statistic is represented as TS_x and is expressed as a percentage.

b. Y_x is the number of data points (out of n) for which the absolute relative error is less than $x\%$ from the model.

c. Larger is the value of the threshold statistic, better is the performance of the model.

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