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SHORT TERM WATER DEMAND FORECASTING: A REVIEW

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ABSTRACT. Water is the most essential commodity for all living beings and is one of the most important renewable resources. Demand forecasts are considered necessary to prepare and optimize the management of resources. Considering the importance of water management, forecasting is of utmost significant. Several techniques have been developed in this domain. Short term water request estimation could be a vital step to back choice making with respect to gear operation administration. 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.

1. INTRODUCTION

For everyone on earth, water is a vital element for life. With the increase in population the demand for water escalate and pressure for finite resources intensifies. Thus increased population, combined with higher standards of living, particularly in the developing countries, will pose enormous strains on land, water, energy, and other natural resources, [1].

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Besides efficient water supply management operation, it is required to have an accurate forecasting method too. Water Demand management aims to reduce the wastage of water due to overuse and leakage. It is generally accepted that water demand is affected by various climatic, socio-economic, government policies and strategy related factors that differ from place to place, thus necessitating the need to develop a city specific models to predict water demand, [2].

The objective of this paper is to present an extensive review of the short term urban water demand forecasting method and model, keeping into consideration a different economic and demographic region. The review covers the models developed using standard statistical techniques, such as linear regression or time-series analysis, or techniques based on Soft Computing (SC) and Extreme learning machine (ELM).

The outline of the paper is organized as follows. The forecasting method will be presented in the next section follows by Discussion discusses the findings of the review and gaps, and finally Conclusions presents some suggestions for possible future research.

2. General Methods for Forecasting

Various demand forecasting models based on a particular method have been developed during the past years. However, brief literature overviews of the forecasting method, forecast horizon, variables and performance parameter have been discussed in Table 1. Some of the important methods and models extract from the literature used for water demand forecasting are summarized in Table 1.

2.1. **Regression Analysis.** 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, [3].

2.2. **Time Series Analysis.** A time series is a sequence of observations on a variable measured over successive periods of time. 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 in [4] mentioned that a time series model forecast 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 a trend and seasonality. Trends are consecutive increases or decreases in measurement over time. A trend could last several, days, months or years. Seasonality is measured over a specific period of time, [5].

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, [4].

2.3. **Artificial Neural Networks.** The development of ANNs was mainly biologically motivated, but afterwards they have been applied in many different areas, especially for forecasting and classification purposes, [6,8]. ANNs are expansively used for forecasting purposes in various provinces and has an exceptional predictive ability [7–10], mentioned the salient features of ANNs, 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, ANNs are universal functional approximators.

ANNs can be classified into various types; among which, only a limited number are used in water demand prediction. One of the most well-liked ANNs in the area water demand forecasting is feedforward neural networks (FNNs). In FNNs multilayered perceptron (MLP) is widely used by the researcher for its accuracy in forecasting, [11]. The back-propagation algorithm is considered first order gradient method that can be used to train MLP. It has been observed that, apart from forecasting MLP, the method is also used in various applications, [12,13].

2.4. **Hybrid methods.** These approaches combine two or more different approaches in order to overcome the drawback of the original technique, [14].

TABLE 1. Summary of Literature Survey

Ref	Technique	Location	Determinants	Output/Observations	Performance Metrics
Regression Based Methods					
[34]	Co-kriging, Kriging with measurement error Bayesian maximum entropy (BME) is used to estimate the regression relationship between water demand and population density	Phoenix, Arizona, USA	Population density	1. Long term annual forecast. 2. Improved forecasting accuracy up to 43.9% over other space-time mapping.	Mean square error (MSE)
[35]	Developed a regression-based water demand models	Seattle, Washington USA	Density, building size, lot size, household size, income, price, temp, rain	1. Forecast monthly water demand. 2. Capable of forecasting single-family residential water demand	Root mean square error (RMSE)
Time Series Based Methods					
[36]	ARIMA Method	Kuwait	Total annual residential water consumption	1. Long term annual forecast. 2. Correlation between socio economic traits and their water consumption. 3. Assist the government to subside water consumption	—
[37]	Stepwise multiple nonlinear regression method	Adana, Turkey	Average monthly water bill, total subscribership, atmospheric temperature, relative humidity, rainfall, global solar radiation, sunshine duration, wind speed and atmospheric pressure	1. Forecast monthly water demand 2. Monthly water demand is directly related to total number of subscribers and atmospheric temperature.	Mean absolute percentage error (MAPE) and correlation coefficient (R).
Artificial Neural Networks					
[38]	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 demand water forecasting.	Mean absolute percentage error (MAPE)
[8]	ANN, regression and time-series models have been developed and compared.	Ottawa, Ontario, Canada	Weekly 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 maximum absolute relative error (max ARE)
[39]	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 model with 99% and 97% respectively accuracy for daily and hourly forecasting.	MAPE
[40]	Time series, regression method, expert system and ANN.	Lexington Kentucky, US	Water demand, temperature and total rainfall	1. Short term daily water demand forecasting. 2. ANN model outperformed expert system followed by time series and regression model.	(AARE) and threshold static (TS).
[41]	ANN, time series and regression	Ottawa, Canada	Maximum daily air temperature and rainfall	1. Short term: peak daily summer water demand forecasting. 2. ANN model outperformed regression followed by time series	AARE, Max ARE, R^2
[42]	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.	(AARE), threshold statistic (TSx), Max ARE, coefficient of correlation (R^2)
Hybrid Approach Based Methods					
[43]	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 learning algorithm, 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 and RF	RMSE, MAE, Nash- Sutcliffe (E) and modified Nash-Sutcliffe (D).
[19]	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	1. Monthly water demand forecasting. 2. PSO-ANN outperforms in terms of fitness function	Performance matrices used for the evaluation of models are RMSE, MSE and MAE.
[16]	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.	MAE and Pearson (r).
[18]	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.	MAPE and determination (R^2).
[30]	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 a short data set. 3. The Developed model improved accuracy between 3% and 11% with respect to previous work.	Standard error prediction (SEP) and R^2.
Extreme Learning Machine Method					
[26]	Extreme Learning Machine	Montreal, Canada	Average daily water demand, maximum temperature, total precipitation and occurrence of precipitation recorded at current day, one day ago, 2-day ago and 3-day ago	1. Short term: current day, 1 day, 2-day and 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 and 3 day lead time water demand forecasting.	RMSE and coefficient of determination R^2.

Combining multiple models can be an effective way to improve forecasting performance, [15]. For performance improvement of the forecasting model, some authors, [16–19] developed hybrid forecasting models based on two or more different models.

Wavelet-bootstrap-artificial neural network (WBANN) modeling approach was proposed by [17] to forecast medium-term urban water demand with limited data. Wavelet transforms and bootstrap combined to form a wavelet-bootstrap-ANN. The bootstrap is a data-driven simulation method that uses intensive resampling with replacement to reduce uncertainties. WBANN model has the potential to increase accuracy and reliability.

Genetic Programming (GP) explains a nonlinear relationship between some parameters; it is one of the well-known methods in AI. In GP a user can find straight mathematical or logical relationships between some input and output. Nasseri et al. in [20] proposed a hybrid model that combines extended kalman filter (EKF) and genetic programming (GP) for forecasting monthly water demand in Tehran. EKF is used for nonlinear transition.

2.5. **Support Vector Machines.** SVM is a learning technique with accompanying learning algorithms that recognize patterns and analyze data, [21]. The basic idea of the SVM model is non-linear trends in input space can be mapped to linear trends in a higher dimensional space and recognizes the subtle patterns in complex datasets by using a learning algorithm, [22]. SVM is not dependent upon the complete training data, and only the support vectors are enough for generalization. SVM-based model selection certainly manages to improve the forecasting results in terms of both errors and bias, [23].

2.6. **Extreme Learning Machine.** ELM is a single hidden layer feed forward neural network, but it does not use gradient descent (or any other method) to tune its parameters. ELM shows that hidden nodes can be generated randomly and need not to be tuned. Compared with the conventional neural network learning algorithm it overcomes the slow training speed and over-fitting problems, [24]. ELM is based on empirical risk minimization theory and its learning process needs only a single iteration. The algorithm avoids multiple iterations and local minimization, [25]. Experimental studies demonstrate that the performance of basic ELM is stable in a wide range of a number of hidden nodes, [24].

3. Discussion

Water demand forecasting is an area that requires high accuracy since the supply of water is dependent on water demand. Several methods have been studied and analyzed including regression analysis, time series, soft computing, hybrid and ELM. However, an insight look at the existing literature suggests that this area still has a lot to offer for water demand forecasting.

Traditional forecasting technique like regression analysis tends to overestimate the demand. This results in over expenditure on water production and transmission infrastructure which are larger than needed, [26]. It has been observed that the conclusion drawn from time series is not always perfect. Factors influenced by time series may not remain identical for longer period of time, hence it is unreliable for forecasting. Time series models, such as autoregressive (AR), moving average (MA), combined AR and MA (ARMA) and autoregressive integrated moving average (ARIMA) are not effective for a real world practical problem which are complex and nonlinear, [18]. Changes in water demand are nonlinear and may not be accurately predicted by linear methods, [27].

Despite many satisfactory characteristics of ANN, building neural network architecture for forecasting is challenging. It has been observed that the learning algorithm, number of input nodes, hidden and output node is crucial for accurate forecasting. ANNs are well suited for issues whose solutions require knowledge that is difficult to specify but requires an expansive volume of data or observations. The design of ANN is more of art than science, [44]. Perhaps without hidden node a simple perceptron with a linear output node is equivalent to a linear statistical model. It is easier to forecast using a large dataset. The noise in the data has less impact on a large volume of data. However, the same cannot be said for a small sample size, [17]. The issue of finding a parsimonious model for a real life problem is critical for ANN because of overfitting problem likely to occur with it. The accuracy of ANN is related to non-linear data, dealing with non-stationary data is yet to be explored, [28].

Even though there are several types of neural network have been proposed since 1980 however, few methods are used for water prediction, [28]. Multilayered FFNs is the most popular and widely used paradigm in many applications including forecasting. BP algorithm is considered a first order gradient method that can be used to optimise parameters in MLP. However, it suffers from a local minimum problem and slow convergence. References are also found for deep neural network, [29] and ELM in [26, 31]. However, no studies using the architecture of Recurrent Neural Networks such as Hopfield, Jordan have been found for water demand prediction. Limited research has been found on particle swarm optimization algorithm. Emphasis should also be given to parametric change in demographic and socio-economic factors that affect demand, explore and identify those factors that are called shift variables in the demand curve.

4. CONCLUSION

In this work, an extensive review of urban water demand forecasting is presented. For obtaining accurate result of forecasting, the model will be applied while looking deep insight of socio-economic and demographic variables of the research region. There is no method or model which guarantees the optimal solution for all nonlinear problems. Immense literature is available for short term forecasting, there are very few studies that address medium and long term forecasting. A neural network learns and does not need to be reprogrammed. Enormous study is available in the domain of ANN there is a lack of literature suggesting the appropriate number of hidden nodes, nodes in hidden layers, optimum value of learning rate and initial weights [32, 33].

MLP networks are used in various applications including forecasting because of their inherent capability of arbitrary input-output mapping. Other influential model Hopfield networks and recurrent network are rarely used in forecasting. So ANN is becoming popular for the prediction of results about certain parameters. Most of the researchers have concluded that artificial neural network and hybrid models generally outperform other predictive models used in water demand forecasting for a city.

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