Artificial Intelligence Approaches for Urban Water Demand Forecasting: A Review

Abdullahi Uwaisu Muhammad, Xiaodong Li(✉), and Jun Feng

College of Computer and Information, Hohai University, Nanjing, China
uwaisabdullahi87@yahoo.com,
{xiaodong.li, fengjun}@hhu.edu.cn

Abstract. In various research fields such as medicine, science, marketing, engineering and military. Artificial intelligence approaches have been applied, mainly due to their powerful reasoning capability, flexibility, modeling and forecasting capacity. In this paper, an attempt to review urban water demand forecasting using various artificial intelligence based approaches such as fuzzy logic systems, support vector machines, extreme learning machines, ANN and an ARIMA as well as hybrid models which consist of an integration of two or more artificial intelligence approaches are applied. The paper illustrates how the different artificial intelligence approaches plays a vital role in urban water demand forecasting while recommending some future research directions.

Keywords: ANN · ARIMA · Forecasting · Water demand

1 Introduction

With rapid increase in world population, per capital income, industrialization and the impacts of global warmings due to climate change on the world [112, 111]. Forecasting of urban water demand will play a vital role in the planning, distribution and management of scarce water resources among competitive users [92]. A hybrid wavelet artificial neural network (WANN) was compared to three AI approaches; conventional sediment rating curve, MLR and ANN. The results illustrated WANN as the most accurate model for suspended sediment load forecasting. Research conducted by [26] proposed a particle swarm optimization (PSO) model while comparing it's relative performance with ANN to forecasting the level of water in river channel. The results illustrate it to serve as a method that is very reliable and efficient in training artificial neural network. Using four different time scales [45], presented a dynamic neural network (DNN) for forecasting urban water demand. The proposed DNN proves to be the most efficient in water demand prediction than ARIMA and ANN feed forward backward propagation with forecasting accuracy best in hourly model.

For water demand prediction [100], applied genetic expression programming (GEP) and SVM. Results obtained proves GEP to be very sensitive in classification of the data, genetic operators with optimal lag time, although the support vector machines models slightly outperformed the GEP models. [61] assess computational intelligence tools based on there ability to effectively support simulation of the social-economic parameters of the complete water resource systems. They as well proposes a specific

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research agenda as a road map for both hydro informatics and adaptive water management. [2] conducted a research by comparing time series analysis and MLR to ANN for peak water demand in summer days in Ottawa Canada. The ANN proved to perform best in prediction of peak summer water demand than the reference models. Being an arid country with harsh climate conditions [60], suggest the government to enhance and implement new policies and strategies that will assist in management of scarce water resources. For proper and efficient and reliable usage of water resources, the government should also be involved in the following activities; water treatment and reuse management, water loss management, public awareness, reducing subsidy policy, incentive pricing as well as inclusion in participation of private sector.

Research conducted by [50] compares a series of predictive models using hourly data set water demand that were obtained from water pumping stations in eastern Spain. The results identify the SVR as the best model followed by MARS, PPR and random forest. As [10] conducted a comparative survey and applied multiplicative season algorithm (MSA) and discrete wavelet transform (DWT) as an alternative data processing techniques. The output of the multiplicative season algorithm and discrete wavelet transform are applied as an input to multi linear perceptron to develop a combined model and compared it with stand alone multi linear perceptron. The results demonstrate that the combined MSA-MLP was found to perform the best through out the prediction lead time. They suggest further research to be taken for short term water demand while taking into consideration weather data and other socioeconomic factors as inputs variables. [96] in there research proves the heuristic model as the best in performance, however integration of 2 or different types of artificial intelligent models helps to improve the precision and accuracy by minimizing error to 15.96%. While [91] reviewed forecasting models for the previous 5 decades and proposed a novel technique that can model the system to reflect the relationship between water demand and macro economic environment. This was practically implemented by applying the research under a recent alternative fluctuation of economic boom as well as down town environment.

A novel technique that can estimate the total amount of dissolve solids, turbidity and electrical conductivity was proposed and applied in Johor river [81]. The model proves to have a greater effect in simulating and forecasting with an absolute error of 10% for streams, lakes, dams and rivers. In another study [88], designed and implemented an intelligent decision support system (IDSS) using hourly water demand data set for water demand management. The AI technique forecasting improves the performance when compared to reference conventional learning models, although they suggest a method for integrating the system to a multi agent system for further research. Research by [40] proposed water demand forecasting model by applying Markov chain, and compared the relative performance of homogeneous and non homogeneous Markov chain (HMC) models with ANN and naive models. The HMC model proves to be distinctly more efficient than the others. The authors suggest estimation of the proposed model's performance to other reference forecasting models using deterministic and probabilistic real life cases. While [48] presents an incremental ELM (IELM) designed to operate based on the principles ELM. The results proves the kernel based IELM to perform best than other online sequential ELM and LS-SVM with enormous data.

An analysis of new technique ANN, regression and time series analysis was conducted by [57] to determine which of the networks is best. The output results obtained establishes the suitability and superiority of the new technique of ANN over the referenced models. The performance of gradient powell-Beale ANN, MLR, resilient back propagation ANN and Levenberg Marquardt ANN using 3 different types of data set; temperature, precipitation and water consumption for six consecutive years was analyzed [6]. The Levenberg Marquardt ANN proves to be more precise, reliable and efficient than the bench mark models. [46] applied WANN and predicted ground water level for the next one year using genetic expression programming. The advantages of monitoring the ground water resources was suggested for future studies. The authors also suggested predicted water budget to be considered for further research on environmental planning. To address water demand forecasting for real time operation [84], applied multi layer perceptron back propagation ANN, dynamic neural networks [DNN], ANN hybrid and DNN Hybrid. The DNN hybrid performed the best with MAE 3.3 L/s and 2.8 L/s for train and test data set respectively for forecasting for the next one hour and 3.1 L/s and 3.0 L/s for train and test data set respectively for the subsequent 24 h respectively.

The rest of the paper is organized as follows; Sects. 2 to 7 provides the basics review and current research trends in urban water demand forecasting using various artificial intelligence approaches i.e. fuzzy logic systems, support vector machines, extreme learning machines, artificial neural networks, ARIMA model and a combination of various hybrid models respectively. Section 8 presents the discussions of the artificial intelligence in details based on the evaluation criteria, scaling pattern applied and input variables. In Sect. 9 we presents the limitations and recommend future research direction. Finally conclusion are discussed in Sect. 10.

2 Fuzzy Logic Systems

Fuzzy logic systems can be defined as formal method of reasoning to approximate reasoning. The process normally involves complexity and uncertainty generally appearing in different forms. The concept applied by a fuzzy logic system is considering the states of the system in the form of subset that are defined by the three special words; I.e. “big”, “medium” and “low” etc. A suitable representation of both simple and complex physical systems can be used in fuzzy rule base [10]. Three main components that made up the architecture of a fuzzy logic system are the fuzzifier, fuzzy database and the defuzzifier. The fuzzifier assist’s in converting the data set from scalars to vectors before executing it within the fuzzy database, the defuzzifier transforms the vectors obtained from the fuzzifier into the real data set. The fuzzy network models are divided into 2 sections; (i) the fuzzy rule base (ii) fuzzy inference system (FIS). The fuzzy rule base are defined by the conditional (IF-THEN) statements while the FIS is further subdivided into 3 main categories depending on the nature of inference operation of the conditional statement which are: Mamdani’s system, Sugeno’s system and Tsukamoto’s system [8]. The membership function of a fuzzy logic enables the model to characterized the antecedents and consequents. They can be illustrated by four commonly used shapes; triangular, trapezoidal, sigmoid and gaussian shapes. These shapes assist in illustrating a clear direction on how the grades varies along the vertical-axis of the models [9].

Fuzzy sets enables the reduction of enormous data set to precise, quantitative and fewer variables which will be utilized by fuzzy logic systems. They also deals with human reasoning as well as analyzing uncertainties in the model. These models needs the least observations than most of the other forecasting models. Incomplete data set can be utilized to generate the predicted output results, although the output results obtained by the fuzzy logic system is not always accepted [42]. [10] conducted a research on fuzzy logic approach for the purpose of making predictions of water consumption in Istanbul city of Turkey. The results obtained proves an overall prediction relative error of less than 10%. A decision support system (DSS) that can be applied for identifying the following process; water reuse potentials, variables for observation of the reclamation of water level using fuzzy logic systems was developed by [9]. From the results obtained, water reuse potential is highly related to water exploitation index, drought, density of the population, waste water treatment and water demand. Considering city plans, nearness to cultural sites, medical facilities, education and transport systems for house pricing in Turkey [63], applied fuzzy logic systems. The results proves fuzzy logic to be able to predict house sale prices for different cities in the world.

By identifying many factors directly or indirectly related to pipe leakage potentials [54], proposes a novel fuzzy based algorithm for forecasting leakages in piped water distribution system for urban cities. The proposed model first implemented for water distribution in Thailand assists water stakeholders to prioritize there rehabilitation strategies of pipe water distribution system while establishing an effective, reliable and efficient method for water leakage control. While research conducted by [55], will have a important impact by assisting water stakeholders in controlling leakages in pipe distribution system within a minimum time after its occurred. This research will also help in prioritizing the management of leakages in pipe distribution systems. By applying fuzzy logic approach for the analysis of electricity energy demand in hydrophos electric power stations [56], reveals the method to be very effective, efficient and reliable. The step by step processes involved in the development of a prototype spatial decision support system (SDSS) was described and conducted by [72]. The output results obtained proves the model's application to compliment engineers in urban water management application while integrating it to users characteristics and site constraints.

3 Support Vector Machines

Support vector machines can be defined as a statistical modeling tool that can be applied for the analysis of both regression and classifications problems. These learning theory do not normally have a special characteristics or structure. The trained data sets are normally judged by there contribution, as such very few section of the trained data contribute to the final model's performance [36]. SVMs minimized the upper bond of the generalized error while regressing functions by utilizing a high set of its linear function [85]. Support vector regression (SVR) are very essential components employed for utilizing support vector machines. They involves mapping the input space s to the high dimensional space Q(s) in an approach that is non linear [80]. The process involves inserting the kernel function so as to avoid another dimension, this enables it to make possible for the model to analyze regression problems. The variables which are the data set applied are the input data plays a vital role as support on the training model [101]. The equation is illustrated below.

$$\mathrm{Y(x) = wK(x) + c} \tag{1}$$

Y(x) represents output response variable, w is the weight vector, K is the kernel function that transforms the support vector in high dimensions, x is the input parameters and c is the bias. The performance of support vector regression depends on setting a regularization and kernel function constants that are excellent. The later assist in changing the dimensions of the input space, thus enabling it execute the regression analysis with high confidence level [36].

In terms of measurement of accurate stream flow and reservoir inflow [68], applied ANN, ARIMA and SVM. The results demonstrate the distinct capability and advantage of SVM in forecasting hydrological data set composed of linear and non linear characteristics. Research titled “Water demand prediction using ANN and support vector machines” by [80], compares two artificial intelligence models for water demand prediction. The results proves ANN to perform significantly better than SVM. A multi-scale relevance vector regression model which is applied for prediction of urban water demand to 2 real water works in Chongqing China was proposed by [15]. The results proves the hybrid model forecast on urban water demand to be more precise and accurate using 3 evaluations criteria; CoC, MAPE and NRMSE. [101] for assessing the usage of phase space reconstruction in there research prior to designing of model’s input data set, designed a support vector machine for prediction urban water demand. The final results obtained, proves optimized lag time of the input data set assist in enhancing the accuracy and effectiveness the model. [25] proposed a water demand forecasting model and adopt a 2 stages learning procedure that operates based on time series data set clustering with SVR. The model which is applied at both aggregated level and individual consumption level proves to be very reliable and efficient on individual data set, due to it’s ability to makes the final results more statistically accurate.

4 Extreme Learning Machines

[52] Proposed a state of art of a simple learning AI algorithm for a feed forward neural network. These algorithm obtained a better generalization performance and are faster than conventional learning algorithms, because they have a greater ability to store regression problems efficiently within a short modelling time, while showing better predictive performances [33, 75]. Extreme learning machine secure the name because the proposed algorithm tend to reach the least in training error, while obtaining the smallest forms of weight as well as best in generalization, they also execute programs faster than conventional learning algorithms [1, 51, 110]. Research conducted by [104]

compared the output results of an ANN and a recently developed ELM for prediction of urban water demand. These models are integrated with wavelet transform (W) or bootstrap (B), ELM, WELM, BELM, ANN, ANNW, ANNB while applying water demand and climate data set from three cities in Canada. The results obtained illustrated the importance superiority of wavelet transformation, due to its ability to improves the accuracy and efficiency of the models. The capability of an extreme learning machine model for estimating streamflow discharge in urban region of Australia was compared with the bench mark ANN models by [32]. Based on there findings, ELM with selected input data set has a good capability for estimating streamflow discharge and they also performs better than ANN model. They suggest the extreme learning model based model to be employed for analyzing the various processes in hydrological stations; such as river flows discharge for efficient and effective usage of water in agricultural lands, developing early warning strategies for drought and flood. [79] performed investigations on the potentials of MLR, ELM, SVR and ANN for short term urban water demand forecasting. Results justifies the superiority performance of ELM, due to its ability to improve in accuracy and precision of urban water demand forecast over the referenced models. They suggest further recommendations to include investigation which models will be more suitable for forecasting long term water demand values in other cities which have different climate characteristics while demanding the applications of ELM in forecasting streamflow discharge, ground water level and rainfall prediction.

A meta ELM which operates in 2 stages was proposed by [65]. The analysis and experimental results provided by the some of the bench mark ELM and ensemble models proves the proposed hybrid ELM model as more effective and efficient than the reference models. The authors suggest further research to include subset resampling selections and meta extreme learning machine model with heterogeneous extreme learning machines. In order to determine the structure of single hidden layer feedforward NN for regression problems [49], proposed an efficient model on error minimized ELM and particle swarm optimization. Experiments results illustrated the proposed model to achieve best generalization and performance with few hidden layer nodes than the reference ELM. They suggest future research work to include the steps involved in solving the problems, as well as applications of the proposed hybrid model for complex classification problems. [113] seven different artificial generated and nine real data sets are applied to estimate the accuracy of the fast incremental ELM models for classifying data streams with traditional algorithms. The proposed method proves to be simplest in structure, and also acquires a higher and more accurate results with least time consumption. The authors suggest to include in there future research to include the procedure of selecting a bridge parameter while ensuring accuracy, speed and stability. [116] proposed a novel approach that integrates the wavelet analysis, kernel extreme learning machines on self adaptive particle swarm optimization (PSO) and an ARMA so as to enhance forecasting performance while applying each of the model's characteristics. The performance of the proposed hybrid model proves it to produce the best performance as its produces more accurate, better generality and practicibility than single models.

5 Artificial Neural Networks

õA data processing, modelling and forecasting techniques that are motivated by the learning steps that takes place in nervous system of the human brain system composed of 3 sections; input, hidden and output layers are called artificial neural networks. These artificial intelligence models can also be applied for the of adaptation of an arbitrary and unknown equations with a degree of precision and accuracy [8, 99]. ANN can also be applied in forecasting future values of possible multivariate time series data set based on past values, and it can be described as a network model of with processing nodes which are interconnected in a specific order thereby assisting it to perform numerical calculations [6, 39, 82]. Without any physical involvement ANN, have the capacity and the means to learn behaviours from examples between the inputs and outputs layers a term referred to as generalization ability. It also has superior characteristics to be able to extract the various patterns obtained between the input and output variables without the need for an explanations [21, 120]. In order to determine the house prices in Turkey [99], compares the relative forecasting ability between hedonic regression and ANN. The study illustrated the ANN as the best alternative for prediction of houses prices.

To address water demand forecasting for real time operation [18, 23] applied ANN in residential water end use forecasting while [84], applied multiple layer perceptron back propagation ANN, dynamic neural networks [DNN], ANN hybrid and DNN Hybrid. The DNN hybrid performed the best with MAE 3.3 L/s and 2.8 L/s for training and testing data set respectively for forecasting for the next one hour and 3.1 L/s and 3.0 L/s for training and testing data set respectively for subsequent 24 h respectively. For modelling, control of water quality and drinking treatment process of water, [20] illustrated the performance of ANN as its captures the non linear characteristics of the process where the micro-scale interactions are not properly understood thereby providing the water treatment plant operators alternatives to scale experiments having the best process operating characteristics. [38] investigated the best fit input structure for predicting water consumption using a series of ANN networks. A new technology to forecast household water demand in China which provides an efficient and reliable method to formulate domestic water demand in urban area was proposed by [70]. The authors suggest for time extrapolation, multi variant method as well as forecasted information on population, income and water prices to be included in future studies.

By merging the output wavelet transform to ANN for crude oil price prediction using 2 main crude oil prices, [102] estimated the relative performance of the hybrid model to regular ANN. In both cases wavelet transform ANN illustrated crude oil prices more efficient and reliable forecast than a single ANN model [62]. A multiple layer feedforward neural network model was presented by [62], for forecasting spot price crude oil prices direction in short duration for three days ahead by finding optimal artificial neural network model structure. The output generated illustrated a very comprehensive crude oil price which is dynamic in nature, this will assist stakeholder and individuals in understanding risk management. By analyzing the learning steps of (back propagation, BFGS, conjugate gradient algorithm) and genetic algorithm [93], compared the relative performance of a single ANN for water demand prediction. Genetic algorithm outperformed the reference models with respect to forecasting.

6 ARIMA Models

The auto regressive integrated moving average (ARIMA) also referred as Box-Jenkin model, is one of the most applied artificial intelligent approaches that are also applicable in analysis and forecasting of time series data set. This is because the model have the ability and is capable of identifying complex patterns while analyzing and forecasting in time series data set [5, 109]. These models transforms the time series data sets into stationary forms by differencing process. For data set to be stationary, it's statistical process most be constant over a period of time [31]. Because it does not assume previous knowledge of any underlying models or relationship as in some methods, the use of ARIMA is uncertain as it depends essentially on past informations obtained from the data set as well as previous error for prediction [7, 85]. The ARIMA equation is normally represented by (p, d, q), where p represents the frequency of auto regressive terms, d is defined as the frequency of non seasonal differences while q represents the lagged forecast errors in the output prediction equation. There are three steps involved in an analyzing ARIMA model are identification, parameters estimation and prediction.

A model which combines wavelet transform, ARIMA and ANN to predict electricity demand and price simultaneously was proposed by [109]. The outputs obtained demonstrated the superiority of hybrid model due to its ability to provide a relevant improvement in water demand and price forecasting accurately when it is compared to other approaches that applied a single framework. [7] compares the forecasting ability of ARIMA and ANN using stock exchange data set. The output results obtained reveals the superiority of ANN over the ARIMA model. [85] proposes a hybrid neural network model that exploits the strengths of SVM and ARIMA models for stock price prediction. The results proves a combination of 2 good models does not necessary produce the best performance. By coupling wavelet transform and ANN [4], compares the relative performance of a proposed model to ARIMA and ANN for ground water level forecasting. The outcome proves wavelet transform ANN as potential and very useful for ground water level forecasting. While [89], applied ARIMA in identifying the relationship in urban water demand and weather variables.

7 Hybrid Models

A combination of two or more models give rise to a hybrid models. Since most of the historical time series data presented in this review paper employs the hybrid models, therefore a thorough review of the various combination of hybrid models are presented below.

7.1 Wavelet ANN (WANN)

One of the most common applied hybrid models is WANN. A mathematical equations that is capable of producing representation of the data set and their relationship, so that the data set can be analyzed is termed as wavelet transform. They also helps in analyzing, removing of unwanted noise from signals as well as in the compression of images. The data sets is broken down by the transformation into its wavelet that is a scale and shifted version of the mother wavelet. They also solves some of the disadvantages of fourier series analysis through capturing important information about the decomposition stages. Two main types of wavelet transforms are; the discrete and continuous wavelet transform (DWT), (CWT).

Wavelet transform also helps by capturing the various characteristics of the target data set while detecting localized information in a non stationary data set. WANN uses as input, data sets which are obtained from discrete or continuous wavelet transform on the original data set. The results of the wavelet decomposition serves as the input for WANN [2, 5, 19, 24, 46, 92, 102, 121]. A pictorial diagram illustrating a hybrid wavelet is represented in Fig. 1 below.

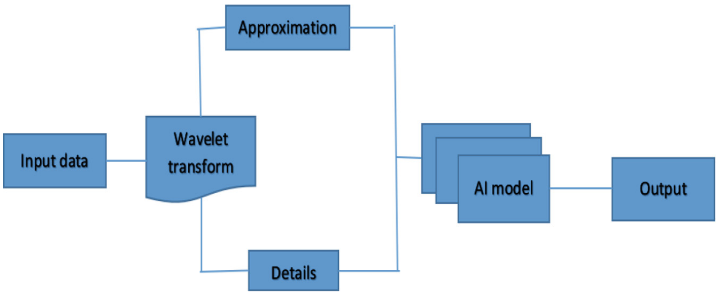

Fig. 1. A pictorial diagram of the hybrid wavelet model for artificial intelligent forecasting [83].

7.2 Adaptive Neuro Fuzzy Inference Systems (ANFIS)

A integration of artificial neural networks and fuzzy inference system is termed as ANFIS. For searching fuzzy rules so for that they can performs well on a given program, these models uses feed forward neural networks (FFNN). ANFIS models have an excellent capacity in categorization, training and production. They posses superiority thus allowing it to bring fuzzy rules learned from the data as well as in making rule base adaptive from numerical data. The results obtained from the ANNs serves as an input of the fuzzy inference system in this model [13, 14, 19, 37, 108, 119]. A hybrid model that consist of an integration of ANN and fuzzy linear regression, which are applied for urban water demand was presented by [14]. The model has shown its superiority over the conventional regression approach. It also proves to be robust against inconsistency and have a higher dimensionality and co-linearity for summer and winter days.

[37] investigated the relative performance of ANN and ANFIS models for predicting ground water level in Iran using 9 years data set. The results proves that, by executing different structures of ANFIS models have the best accuracy by having least number of errors, especially when it applied trapezoidal function and the hybrid methods. [108] presents a methodology to forecast consumers demand of water supply using 6 different models of ANFIS system while considering number of membership functions and the duration. The output result uncovered, the performance of ANFIS significantly improve with increase in input parameters.

7.3 ARIMA+SVM

[85] proposed a hybrid model which is composed of an integration of ARIMA an SVM models. The hybrid model captures both the characteristics and capabilities in the domains of the ARIMA and SVM. It can also model linear and non linear characteristics with overall enhanced prediction.

7.4 Wavelet+ARIMA+Neural Networks

In there research [109], combined wavelet transform, ARIMA and neural networks model for capturing the underlying patterns of the different networks. The proposed hybrid model algorithm is executed for the feature selection on each wavelet sub series data set with the NN using the best candidature for forecasting. The authors proves the proposed model to provide an improvement in both water demand and price forecasting accurately when it is compared to other models using a single AI model approach.

7.5 Wavelet SVM/R

The wavelet SVM are models that uses as input data set that were obtained from wavelet transform. Some of the advantages of wavelet transform are assisting in denoising, compression and decomposition of the data set. Thus the separation of some features in wavelet transform helps to exploit the underline patterns of original data set. All data set applied to SVM for forecasting proves the best performance when compared to other models ANN, SVM, WAMM, WSVM [36, 121]. Comprehensive comparison and discussion of WSVM, WANN, ANN and SVM by [121], proved that, wavelet preprocessed improves the forecasting capability and efficiency of the models. The WSVM provided more precised and reliable groundwater depth prediction with WANN close in some single coefficient.

7.6 SVR+Adaptive Fourier

In order to improve the prediction of SVR [23], built on top of the support vector regression model a fourier series. The output of the fourier series serves as an input to support vector regression thus helping the hybrid model to better adjust the maximum and minimum water demand peaks and captures part of the data set that the support vector gression cannot be able to reproduce. The proposed model proves to be an important tool for water utilities due to its ability to allow operators to program reliable manoeuvre so as to minimize the use of water and energy.

7.7 ANN+Time Series Model

The hybrid model presented in this subsection consist of ANN and time series model. For enhancement of ANN and fourier series, the output results of ANN obtained is feed into the time series model. The authors proved that, combining ANN with time series produces the best output compared to the individual usage of ANN and time series models [12].

7.8 Wavelet+Multiple Linear Regression

Multiple linear regression was applied to model the linear characteristics and relationship between dependent and independent variables. [36] applied the output of the wavelet transform as the input of the multiple linear regression. While [36], applied hybrid WNNs, wavelet linear regression (WLR), WSVR and compared with MLR, support vector regression and time delay neural networks for ground water level simulation for 2 wells in Iran. The study reveals wavelet improving the training of the neural network.

7.9 Wavelet+ANFIS

To improve the accuracy of there model, [19] applied wavelet pre processed data were used as input to ANFIS model. The data set that were decomposed were executed individually in the ANFIS model. By integrating the decomposed wavelet to ANFIS, the output results of the WANFIS were obtained. [19] compares the performance of ANN, ANFIS, WANN, WANFIS models for forecasting salinity in river basin using 28 years data set for conducting the practicals on the artificial intelligence models. The hybrid WANN and WANFIS models outperformed the reference models in predicting water salinity indicating the advantages of wavelet transforms.

7.10 Bootstrap NNs+Wavelet Bootstrap NNs

A data driven process that can simulate the multiple realization process from a given data set of a process is defined as bootstrap [105]. In bootstrap NNs the output results obtained from the bootstrap is applied as the input to the AI model. Thus enabling the model to obtain better results than NNs, due to it's ability to enhance the capability of the bootstrap. The bootstrap NN reduce the uncertainty of forecast and the performance of the forecasted confidence band are more accurate and reliable.

7.11 WBNNs

The model takes both the advantages of the capabilities of the of bootstrap re sampling and wavelet transformation techniques to form a single model. [105, 106] proposed a hybrid WBNN for prediction of water demand. The relative performance of the hybrid model is compared with ARIMA, ARIMAX, conventional neural networks, WNNs, bootstrap NNs and simple naive persistence index model. Results obtained demonstrated the hybrid wavelet bootstrap NN and wavelet analysis NN produce more accurate results. The bootstrap NN reduce the uncertainty of forecast and the performance of the forecasted confidence band are more accurate and reliable.

[12] compared time series networks, time series general regression NNs and general regression NNs for domestic water demand using data set obtained by meteorologist. The results proved that, temperature as the most important meteorological factor while rainfall as the least for training the model. Also time series general regression neural network produced the best results when they are compared to a individual time series and ANN models.

TSM = time series model, WTBM = wavelet transform base models, MAPE = Mean absolute percentage error, CoC = coefficient of correlation, CoE = coefficient of efficiency, CoD = coefficient of determination, MAE = mean absolute error, RMSE = root mean square error, AARE = average absolute relative error, RBF = radial basis function, RPE = relative percentage error, CoV = Coefficient of variation, ELM = extreme learning machines, GRNN = generalized regression neural network, WSVR = wavelet support vector regression, SVM = support vector machine, MLR = multiple linear regression, NSE = Nash sutcliffe efficiency, AAE = average absolute error, WANN = wavelet artificial neural network, ARE = average relative error, LR = linear regression, FFNN = feedforward neural network, GA = genetic algorithm, LSSVR = least square support vector regression, WLSSVR = wavelet least square support vector regression, WBANN = wavelet bootstrap artificial neural network, GNP = gross national product, WLR = wavelet linear regression, FNN = fuzzy neural network, WMLR = wavelet multiple linear regression, GP = genetic programming, SVR = support vector regression, DANN = dynamic artificial neural network, KPLS = kernel partial least square, WT = wavelet transform, PLS = partial least square, FTDNN = focused time delay neural network, HP = Hodrick prescott filter, VC OS-ELM = variable complexity online sequential extreme learning machines, SDARE = standard deviation of the absolute relative error, SSE = sum of square error, MGM = multiple step gradient method, VsSVR = variable structure support vector regression, MSRVR = multi scale relevance vector regression, DWT = discrete wavelet transform, NLR = non linear regression, WANN = wavelet artificial neural network, IoA = index of agreement, BoM = bank of models, OLS = ordinary least square regression model, MSE = mean square error, RCGA = real coded genetic algorithm, SOGA = structure optimization genetic algorithm, RCGA = real coded genetic algorithm, SOGA = structure optimization genetic algorithm, FCM = fuzzy cognitive maps, NRMSE = normalized root mean square error, WANN = wavelet artificial neural network, GRNN = general regression neural network, RF = random forest, WBNN = wavelet bootstrap neural network, WANN = wavelet neural network, GP = genetic programming, PDP = percentage deviation in peak, WELM = wavelet ELM ANFIS = adaptive neuro fuzzy inference system, BNN = bootstrap neural network.

8 Discussion

Due to artificial intelligence ability to improve the efficiency and effectiveness of the modelling process, the input layer is considered as the most important layer of a neural network. A very important factor in water price prediction is selection of input data sets. The process which is normally done depends on the knowledge of the artificial intelligence model and availability of data. The frequency of some common input variables applied in the reviewed article is illustrated in Fig. 2. As it can be seen, due to difficulty of acquiring some input data such as water quality, humidity and pressure due to lack of sensors and other privacy concern. Input data sets for instance water demand, precipitation, temperature and population figures are the most frequently applied input variables in water demand forecasting.

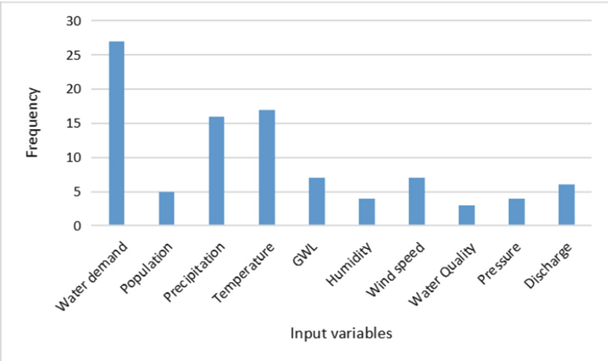

Fig. 2. Frequency of the input variables applied in the reviewed papers.

The time scale represents the sampling interval of sensors applied for the purpose of taking reading of various articles reviewed. The scaling pattern on the input variables applied in urban water demand forecasting are mainly divided into hourly, daily, weekly, monthly and annually. The most common applied time scale according to Fig. 3 is daily followed by monthly then hourly with the least being annual. The daily scale pattern is mostly applied due to the fact that it provides a more comprehensive information on urban water demand forecasting while the annual scaling have the least frequency due to its nature to focus on short term prediction.

Evaluation metrics are performed for the estimation of efficiency and effectiveness of the different artificial intelligence models. According to [29], evaluation is normally conducted with respect to closeness of fit and in most of the cases with respect to observations recorded. It is defined as a method of quantitative assessment, it defines what is to be measured as well as providing the process that are to be used to perform such operations. The frequency of the different standard evaluation criteria are performed as illustrated in Fig. 4. The most common ones are RMSE, MAPE, MAE, CoC, CoE, NSE and MSE.

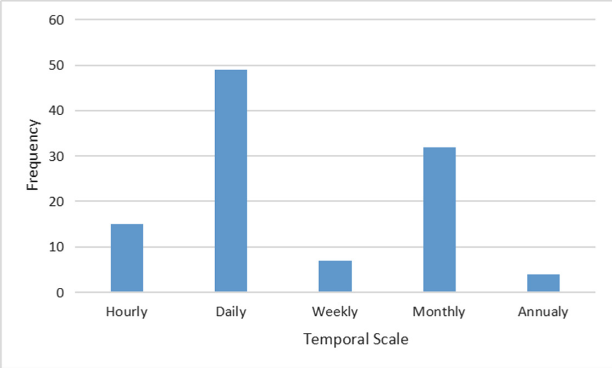

Fig. 3. Frequency of scaling applied in the reviewed papers.

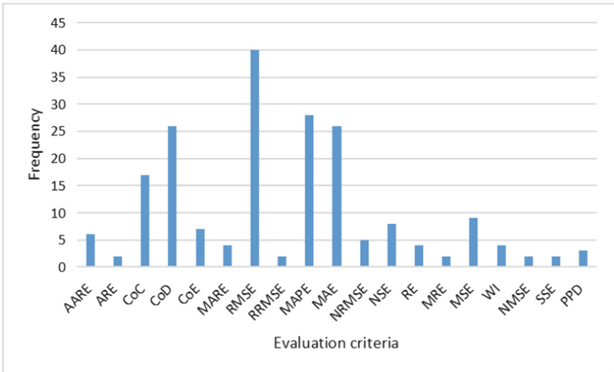

Fig. 4. Frequency evaluation criteria applied in the reviewed papers.

Although various studies have indicate increase in urban water demand due to factors such as global climate change, rapid urbanization, population growth and industrialization among others. This results to an increase in environmental concern for future generations, but the condition will not continue to rise forever due to environmental public awareness, economic recession of some nations as well as industrial saturation. Table 1. summarizes the various artificial intelligence of some selected articles, including authors, artificial intelligence approaches, location, input variables, evaluation criteria and temporal scale.

Table 1. Details of AI reviewed papers including authors, AI approaches, location, input variables, evaluation criteria and temporal scale.

Authors	AI approaches	Location	Input variables	Evaluation criteria	Temporal scale
[2]	ANN	Canada	Climate variables, water demand, population	AARE, Max ARE, CoD	Daily
[3]	Continuous wavelet transform	Canada	Water demand, precipitation, temperature	Fourier and cross spectral analysis	Daily
[4]	ANN, WANN and ARIMA	Canada	Precipitation, temperature and GWL	RMSE, CoE, CoD	Monthly
[5]	WANN, ARIMA, ANN and MLR	Canada	Water demand, precipitation, temperature	RMSE, CoD, RRMSE, Efficiency index	Daily
[6]	Multi variate regression and ANN	Cyprus	Water demand, temperature and rainfall	Max ARE, AARE, RMSE, CoD	Weekly
[9]	Fuzzy logic	Various cities	Water demand, population	Drought and water exploitation index	Monthly
[10]	Season algorithm, WTBM	Turkey	Water demand	RMSE, CoE	Monthly
[11]	Fuzzy logic	Turkey	Water demand	Average RPE, ARMSE	Monthly
[14]	Fuzzy linear regression, ANN	Iran	Water demand, climate	MAPE	Daily
[15]	MSRVR, FFNN, GRNN	China	Water demand	MAPE, CoC, NRMSE	Daily
[16]	SVR, VsSVR	China	Water demand	MAPE, RMSE, MAE	Daily
[17]	MLR, adaptive heuristic and transfer noise model	Netherland	Water demand, temperature	Relative error, MAPE, NSE	Daily
[19]	ANN, WANN, ANFIS, WANFIS	Iran	Water quality parameters	CoD, NSE, TS, NRMSE	Monthly
[20]	ANN	Canada	Water quality	MAE	Daily
[22]	LR, MLR, ARIMA, ANN	Canada	Water demand, temperature, precipitation	AARE, Max ARE, CoD	Weekly

(*continued*)

Table 1. (*continued*)

Authors	AI approaches	Location	Input variables	Evaluation criteria	Temporal scale
[23]	SVR+fourier time series	Brazil	Water demand, wind, precipitation	RMSE, MAE	Hourly
[25]	SVM	Italy	Water consumption	MAPE	Daily, hourly
[26]	ANN	China	Water level	RMSE, mean relative error, CoE	Daily
[27]	ARIMA, MLR	USA	Water demand, population, precipitation, temperature	Ordinary least square regression	Daily, monthly
[28]	GA, RBF, SVM	China	Water demand	MAPE	Daily
[30]	ANN, FFNN, MLP, RBF	Nil	Hypothetical	MSE, CoD, MAE, CoE, mean square relative error	Daily, monthly
[32]	ANN, ELM	Australia	Precipitation, temperature	MAE, CoD, NSE, Willmotts index	Monthly
[34]	WELM, WANN, ELM, LSSVR, WLSSVR, ANN, wavelet decomposition	Australia	Precipitation	RMSE, NSE, MAE, Willmotts index, PDP, CoC	Monthly
[35]	MLR	Zimbabwe	Population, rainfall, GDP	CoV	Monthly
[36]	ANN, MLR, WLR, WANN, SVR, WSVR	Iran	Ground water level	NSE, RMSE	Monthly
[37]	ANN, ANFIS	Iran	Precipitation, irrigation return, flow pumping rate	RMSE, CoD, MAE	Monthly
[38]	ANN FFNN, GRNN, cascade correlation NN	Turkey	Water consumption	AARE, NRMSE	Monthly
[41]	Base and season use model, auto regression model	Australia	Water demand, temperature, rainfall	Standard error, CoD	Daily
[44]	DANN, k-nearest neighbour model, FTDNN	Iran	Water demand	SSE, MSE	Daily, monthly, weekly

(*continued*)

Table 1. (*continued*)

Authors	AI approaches	Location	Input variables	Evaluation criteria	Temporal scale
[45]	ARIMA, DANN, ANN	USA	Water demand, weather variables	MAPE	Hourly, daily, weekly
[46]	WT-ANN, WT-GP	Iran	Water level	RMSE, NSE, MAE	Monthly
[47]	ANN, fuzzy model tree technique	India	Water level, water demand, discharge	CoC, RMSE	Daily
[53]	ARMA, WT-KPLS-ARMA, WT-PLS-ARMA KPLS	China	Water demand for industrial, domestic and agriculture	MAPE	Annual
[57]	ANN	India	Water demand, temperature, rainfall	MARE, AARE, TS	Weekly
[58]	LS SVM	China	Temperature, precipitation, discharge	MSE, MRE	Hourly
[59]	ARIMA, ARIMA+e smoothing	Sri Lanka	Water demand, population	CoC, CoD, RMSE, NSE	Hourly
[64]	FNN, MLR, MLR+MLR, HP-MLR+FNN, HP-FNN+FNN	China	Population, temperature, water demand, greenery coverage, GDP	Relative error	Annual
[66]	OS-ELM, OS-MLR	Canada	Discharge, wind speed, GWL, temperature, precipitation, humidity	MAE, RMSE, NSE	Daily, monthly annual
[67]	OS-ELM, VC-OS-ELM		Discharge, wind speed, GWL, temperature, precipitation, humidity, snow depth	MAE, RMSE, NSE	Daily, monthly annual
[68]	SVM, ANN, ARIMA	China	Streamflow discharge	RMSE, CoC	Monthly
[69]	ANFIS, fuzzy theory	China	Water demand for industrial and commercial operations, weather, population	Fuzzy rules	Hourly
[71]	ANN, ANFIS	India	Discharge	CoC, RMSE, NSE	Monthly

(*continued*)

Table 1. (*continued*)

Authors	AI approaches	Location	Input variables	Evaluation criteria	Temporal scale
[73]	ANN, WANN	India	Discharge, rainfall, temperature,	NSE, RMSE, MAE, PPD	Daily
[74]	ANFIS, multi variate analysis	Greece	Temperature, rainfall, wind speed, water demand, tourist	RMSE, MSE, MAE, MAPE, mean error	Daily
[76]	ANN	Iran	Temperature, precipitation, humidity, pressure, wind speed, population	MAPE	Daily
[77]	MLR, DWT, MLT+DWT	USA	Humidity, water demand, temperature, rainfall, wind speed	CoD, RMSE, MAPE	Daily, monthly
[78]	Constant rate model	UAE	Water demand, population, temperature, precipitation	SDARE, AARE	Daily, monthly
[79]	MLR, SVR, ANN, ELM	Canada	Rainfall, temperature, water demand	RMSE, CoD	Daily
[80]	ANN, SVM	South Africa	Water demand, population	Support vector genius, artificial neural genius	Daily
[81]	ANN	Malaysia	Water quality	SSE, MAPE	Daily
[84]	ANN, DNN, ANN-H, DNN-H, H = hybrid	Brazil	Water supply, temperature, humidity	MAE, pearson coefficient	Hourly
[86]	SOGA, RCGA, FCM, FCM +SOGA+ANN	Greece	Temperature, tourist arrivals, rainfall, water demand	MAE	Daily
[87]	FCM, RCGA, MGM	Greece	Temperature, tourist arrivals, rainfall, water demand, wind speed	MAPE, RMSE, MAE, MSE	Daily
[88]	ANN	Spain	Water demand	MAPE	Hourly
[90]	MLR, ANN, exponential smoothing, ARIMA	Spain	Water demand, temperature, precipitation, humidity, sunshine duration, wind speed	CoD, CoE, average relative variance, percentage standard error of prediction	Daily
[92]	ANN, MLR, WANN, conventional	USA	Suspended sediment load, river discharge	CoD, MAE	Daily

(*continued*)

Table 1. (*continued*)

Authors	AI approaches	Location	Input variables	Evaluation criteria	Temporal scale
	sediment rating curve				
[93]	ANN, Naive, BoM, QMMP +kNN, Holt winters GA	Spain	Water demand	RMSE, MSE, MAPE, MAE	Hourly
[94]	WTGA NN, GA optimised ANN	India	Discharge	RMSE, NSE, discrepancy ratio	Daily
[95]	ARIMA, LR, naive, ANN, Holt winters, RCGA FCM	Poland	Water demand, temperature, precipitation	MAPE	Daily
[96]	ARIMA, parallel adaptive weighting strategy and heuristic	Portugal	Water demand	MAPE, CoC	Hourly
[97]	SVM, ANN, NLR, ELM	Canada	Pipe attributes	CoC, CoE, IoA, RMSE	Annual
[98]	WANN, MLR, ANN, WMLR	India	Discharge	NSE, MAE, CoD, RMSE	Daily
[100]	GP, SVM	Canada	Water demand, population, temperature, wind speed, humidity, precipitation	RMSE, CoD, MAE	Monthly
[101]	SVM	Canada	Water demand, precipitation, temperature	CoD, RMSE	Monthly
[103]	ANN, adaptive sugeno fuzzy, ANFIS	Iran	Water demand, temperature, precipitation, sunshine duration, dew point, wind speed, pressure	CoC, MSE, NMSE, MAPE	Daily
[104]	ELM, ANN, WELM, WANN, BANN, BELM	Canada	Temperature, water demand, precipitation	MAE, PDP, CoD, RMSE	Daily
[105]	ARIMA, ARIMAX, BNN, NN, naive persistence	Canada	Water demand, temperature	RMSE, MAE, percentage deviation in peak,	Daily, weekly, monthly

(*continued*)

Table 1. (*continued*)

Authors	AI approaches	Location	Input variables	Evaluation criteria	Temporal scale
	index, WBNN, WNN			precipitation, CoD	
[107]	ANN, DNN, ELM, RF, MLR, Gaussian process regression	EU	Temperature, humidity, wind direction and speed	RMSE, R-squared, MSE, MAE	Hourly, daily
[108]	ANFIS	India	Water demand	RMSE, MAPE, CoC	Daily
[114]	System dynamics	China	Water demand, population, economic development	Relative error	Daily
[115]	ARIMA	Turkey	Industrial, agricultural, commercial water demand, pipe lines, dams	MAPE	Daily, Monthly
[117]	ELM, GRNN, SVR	Iraq	Discharge	Willmotts index, RMSE, MAE, NSE, CoC	Monthly
[118]	MR, NLR	Turkey	Water bill, temperature, humidity, rainfall, global solar radiation, pressure, water demand, sunshine duration	MAPE, CoC	Monthly

9 Recommendations for Future

From a thorough review of over 100 most recent and cited research articles from high impact journals. We state some limitations as well as suggest some future recommendations as follows:

- Some basic information on each of the artificial intelligence approaches presented in this study on urban water demand management are not provided in detail. The main reason is due to the fact that, the articles reviewed does not provide the overall picture of each of the models due to it been limited between 2008 to 2018. But we have tried to be as comprehensive as possible, while giving good applications that demonstrated the usefulness and applications of each model as solutions to urban water demand forecasting.
- We suggest future research to include the effects of climate variables such as pressure, humidity, temperature as well as water demand and population and

incorporate these data while taking there advantages to determine there relationship at multiple scales.

- Rather than focusing on error based evaluation criteria in evaluating the artificial based approaches. We suggest future research to apply evaluation based criteria based on non error based to measure the performance of the models.
- We also suggest the hybridization of novel artificial neural network model with other non expert systems for urban water demand prediction.
- The analysis of the advantages and disadvantages of each accuracy assessment to the nature of forecasting urban water demand problems can be an interesting area for future research works [43].

10 Conclusion

Recent research on urban water demand forecasting applied by different artificial intelligence approaches such as artificial neural network, ARIMA, extreme learning machines, fuzzy logic systems, support vector machines and an integration of two or more artificial intelligence approaches such as WBNN, ANFIS, WANFIS, WSVR, WMLR, ARIMA + SVM, SVR + adaptive fourier, ANN + times series model, Wavelet + ARIMA + NNs and BNNs + WBNNs from 2000 to 2018 are presented. More focus have been presented to wavelet transform, due to it's ability to assist in denoising while decomposing, manipulating and analyzing signals at different frequency bands and resolutions. Wavelet transform also helps to improve the efficiency and reliability of the AI model. The reviewed papers proves that, there is no single artificial intelligence or hybrid model that seems to be the overall best in performance for urban water demand forecasting.

The research also provided an analysis on over 100 most recent and cited research articles from high impact journals while providing guidance to researchers, academicians, households and water utility managers on urban water demand management. The reviewed papers affirmed that, urban water demand forecasting can be of positive impact for capital investment, revenue collection analysis and generation as well as market management for future generations. The paper also proves that artificial intelligence can successfully be applied for urban water demand forecasting while presenting some future research directions.

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