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State-of-art implementation of computing intelligent models for water demand modelling: A decade review and future direction

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Abstract: The main insight from this research is that there has been significant progress in the development of computer-aided models for water demand modelling over the past two decades. These models are used to balance water demand and supply, which is critical for effective water supply management systems. The equilibrium is achieved through various measures, many of which involve the use of forecasting tools. Recent research on urban water demand forecasting using artificial intelligence (AI) models is discussed in this article, to present the 'state of the art' on the issue and provide some insights and suggestions for future research on methodologies and models. The review examines models developed using traditional statistical methods, including artificial neural networks, linear regression, and time-series analysis, as well as soft computing techniques. This paper demonstrates that the study is focused on a decade-long evaluation of operating system management, indicating an opportunity for long-term projections. It goes without saying that no single model outperforms all the others; however, it is vital to assess the strengths of each model or combination of models for each country or region to determine which model works best in that location. Although the usage of AI and machine learning (ML) has increased significantly in recent decades, there is still potential for development in the field of water demand forecasting.

Keywords: artificial intelligence, computing intelligent models, decade review, machine learning, soft computing, water demand prediction

INTRODUCTION

Water demand refers to the amount of water required by individuals, households, businesses, and industries to meet their various needs. This includes drinking, sanitation, irrigation, and industrial processes. Various factors, including population growth, economic development, and shifts in lifestyle and consumption patterns influence water demand. In many parts of the world, water demand is increasing, putting pressure on already scarce water resources and highlighting the need for sustainable water management practices. Water is a necessity for human need and survival as well as many industries. Sea water is the largest body of water on the planet, but most human activities require freshwater. The majority of freshwater, however, is caught by glaciers and polar icecaps (Souza Groppo de, Costa and Libânio, 2019).

Safe and potable water is one of the most essential elements of nature to maintain life and from the beginning of urban civilisation, settlements have always been chosen taking into account the availability of water to residents of the city. Furthermore, the water supply started falling short of demand due to urbanisation. Water is a critical resource for societal growth and development. The prediction of daily water needs is a valuable tool in reserving water in the city (Sunusi, Abba and Iesha, 2016). Consumer water needs are typically not measured on a sufficiently large temporal and spatial scale to support real-time decision-making. A while ago, approaches to estimating unobserved demand using observed hydraulic data have been developed. Although time series modelling has the potential to represent system-wide demand, it is rarely evaluated on a spatial scale suitable for representative real-time modelling (Ghalehkhondabi *et al.*, 2017).

Access to safe water is a significant challenge, particularly in urban areas. Due to the lack of proper urban planning, some major cities develop haphazardly, which results in the loss of vegetation cover and soil impermeability, and as such, results in global warming. Models are not generally evaluated on a spatial scale suitable for representative real-time modelling. As a result of global warming and the contamination of the origin of the safeguarded water locations, it has become insufficient to meet demand. Due to that, water supply channels are mostly sited in the suburbs of a city thereby making water treatment more difficult and costly (Oyesanmi, 2017). Water demand prediction is very significant; this is why large numbers of experts while ago, have begun to analyse it, as postulated by Ghalehkhondabi *et al.* (2017).

According to Web of Science, a reasonable number of published journals have experienced an exponential increase over two decades. This increase could be attributed to the increasing shortage in the supply of water as well as the development of the relevance of water to human needs. The gap between water needs and supply requires skilled provision of water management system methods. The interval is acquired via operational work. Most of them require the application of the concepts and tools of forecasting such as artificial neural network (ANN), support vector machine (SVM), fuzzy logic etc. which will be explained later in the context of this review (Oyesanmi, 2017).

This paper reexamines recent discoveries on water demand forecasting for city inhabitants using artificial intelligence, with the purpose of presenting the 'newest technique' on the issue and giving research and professional sanitation firms some direction on methodologies and models. This paper describes models developed using standard statistical methods or soft computing-based methods such as linear regression and time series analysis. This review shows that the research focuses primarily on operating systems management. Therefore, there is an avenue for long-standing predictions. Furthermore, there is no single world-acceptable model that goes beyond all techniques in most cases (Pham *et al.*, 2019; Mohammadi *et al.*, 2020). Each region should be analysed individually and the capability of each newly invented model or the application of two techniques should be merged and evaluated. The statistical application of machine learning and AI techniques has improved significantly a while ago (Abba, Nourani and Elkiran, 2019; Elkiran, Nourani and Abba, 2019; Hadi *et al.*, 2019; Abba *et al.*, 2021; Malik *et al.*, 2021). Further, advancement in water demand forecasting still has an avenue for improvement.

The main objective of this paper is to evaluate and review the application of AI in the field of water demand which will be able to provide some guidance to upcoming researchers. A decade review will be carried out to provide the best model to be used globally or in a particular country. The performance of the models using performance criteria will be compared to other models (single or hybrid) and the outperforming model will be suggested in the particular region, state or country. Water demand is still considered one of the major challenges facing most of the countries in the world. Several research studies have been carried out in the field of AI to curtail this challenge and to find a global solution but due to the climatic differences and other atmospheric conditions, there is still no global solution. A summary of the current state of research done in the field of water demand will be reviewed and the best performing models will be adopted.

A bibliometric network based on the reported studies in the Scopus database (1987–2022) was visualised for an extensive literature review regarding the generalisation of soft computing models to handle chaotic water demand applications. In Figure 1, it has been shown that the network visualisation of conducted reviews on water demand vividly depicts that an AI-based approach is receiving a lot of attention. Over 1914 clustered keywords and probability of occurrences were presented, demonstrating the topic's weight and significance in water demand prediction models. The 1914 keywords showing the total strength of the co-occurrence with other keywords were calculated and the one with the greatest total link strength was selected.

ARTIFICIAL NEURAL NETWORKS

An artificial neural network (ANN) is a biologically inspired model that uses interconnected mathematical nodes or neurons to form a structure and can also relate input and output parameters (Ozveren, 2016). Usually, signals having varying intensity are fed through the neuron or node to form a net input into another neuron, and the output layer which equals the number of desired outputs is determined by weight and bias associated with links among the neurons (Uzun et al., 2017) (see Fig. 2). Because of a range of variables, ANN are exceptionally helpful predicting tools. The first is associated with the demand for fewer theories as compared to classical statistical approaches. The generalisation of results and projection of data that has not yet been observed is the second module (Xu *et al.*, 2019; Okeke *et al.*, 2022). The ability to deal with varying degrees of non-linearity in water needs data is a third factor to consider. That is, they are able to accurately represent very nonlinear data correlations and assess nonlinear functions. According to Adamowski and Karapataki (2010), the ANN allows the use of previous data to forecast future values of potentially noisy multivariate time series. To anticipate water use in California metropolis, Ghiassi, Zimbra and Saidane (2008) developed a dynamic artificial neural network approach. The feedforward architecture is a subtype of this dynamic method feedforward neural networks (FFNN). The suggested technique outperformed the autoregressive integrated moving average (ARIMA) and

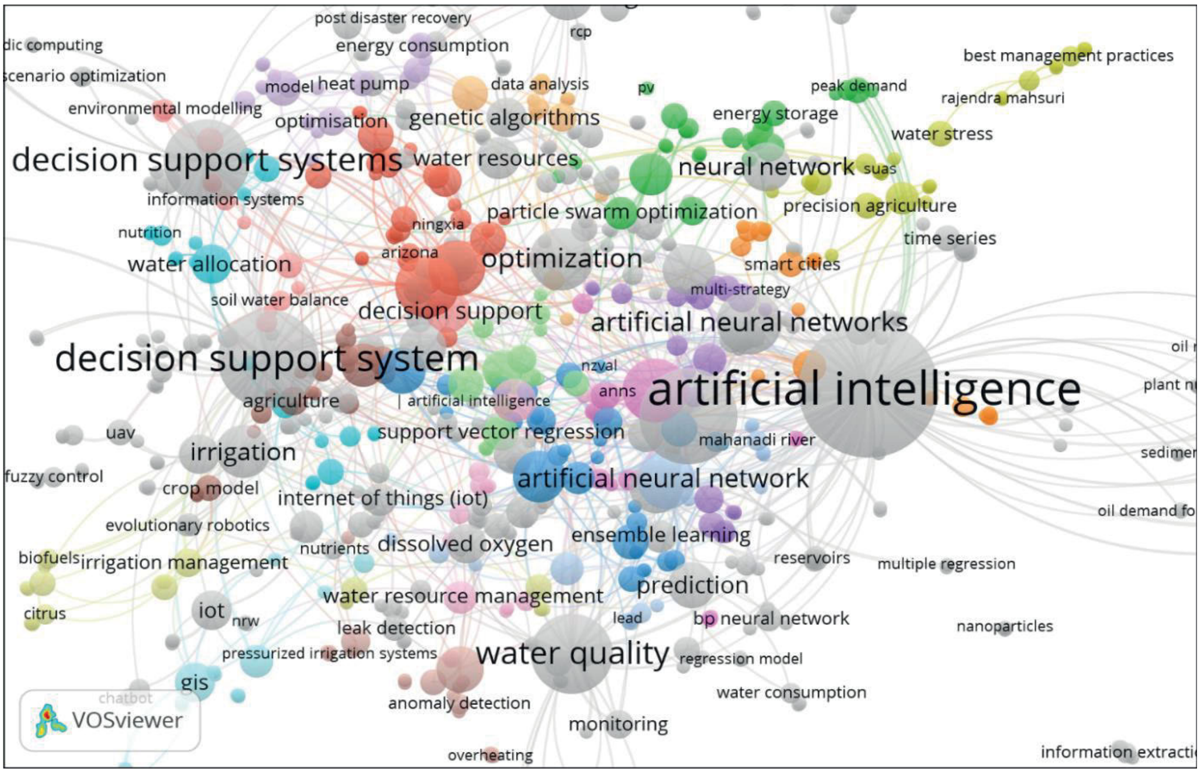

Fig. 1. A bibliometric network on water demand models in Scopus database (1987–2022); source: own elaboration using VOSviewer

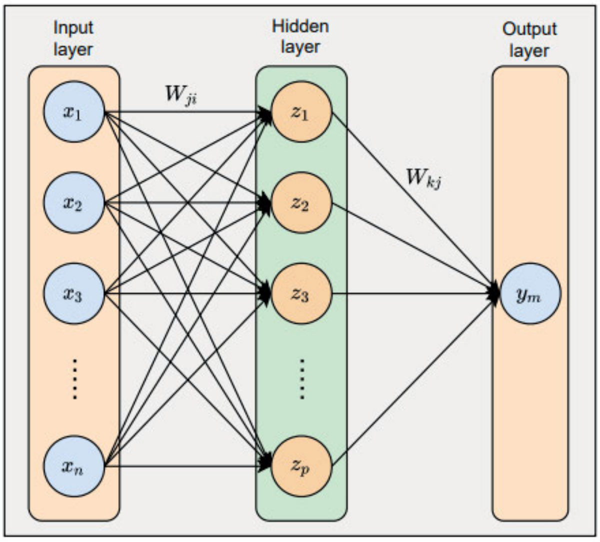

Fig. 2. A typical three layers ANN structure; x_1 = first input feature, z_1 = first hidden neuron, y_m = final predicted output, w_{ji} = weight between input and hidden neuron; source: own elaboration

ANN methods in forecasting water demand, suggesting that it is more effective. These findings suggest that dynamic artificial neural network, version 2 (DAN2) is exceptionally good at forecasting urban water demand across a wide range of time periods.

ADAPTIVE NEURO-FUZZY INTERFERENCE SYSTEM

The adaptive neuro-fuzzy interference system (ANFIS), formerly referred to as the Takagi–Sugeno–Kang system, was created by Jang in 1993 and is a widely used fuzzy inference system (Baghban and Ebadi, 2018) (Fig. 3). It comprises five components: input(s), a fuzzy system generator, a fuzzy inference system (FIS), an adaptive neural network, and an output (Onifade et al., 2022). This technique uses the hybrid learning or back-propagation algorithm for training and combines the features of neural networks and the capabilities of fuzzy logic (Dashti et al., 2019). Altunkaynak, Özger and Çakmakci (2005) forecasted monthly water consumption in Istanbul using the fuzzy Takagi-Sugeno

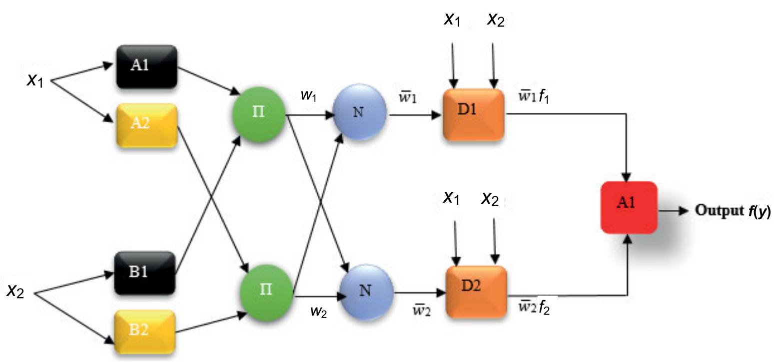

Fig. 3. Overall structure of adaptive neuro-fuzzy interference system; x_1 = first input variables, x_2 = second input variables, A1 = fuzzy membership functions (MFs) for low input x_1, A2 = MFs for high input x_1, B1 = fuzzy MFs for low input x_2, B2 = MFs for high input x_2, Π = product nodes, N = normalisation nodes, D1 = rule 1 consequents (linear functions), D2 = rule 2 consequents (linear functions), w_1 = rule 1 firing strength, w_2 = rule 2 firing strength, $\bar{w}_1$ = rule 1 normalise firing strengths, $\bar{w}_2$ = rule 2 normalise firing strengths, $\bar{w}_1 f_1$ = contribution of rule 1, $\bar{w}_2 f_2$ = contribution of rule 2, f_1 = first consequent functions, f_2 = second consequent functions, $f(y)$ = final ANFIS output (defuzzified crisp value); source: own study

(FTS) technique (Turkey). Water usage figures from the preceding three months are used as independent variables in this strategy. That is, changes in demand from the previous three months determine water demand for the coming three months. According to the authors, this model is more widely utilised than the Markov or ARIMA techniques, which are typically used for stochastic modelling and forecasting. Using the FTS technique rather than ARIMA has the advantage of avoiding assumptions regarding stationery and ergodicity.

SUPPORT VECTOR MACHINES/REGRESSION

Support vector machines (SVM) are supervised machine learning models with a powerful regression tool that have been used to solve a variety of prediction problems in a variety of domains (Onifade *et al.*, 2022). In SVM, nonlinear kernel functions are used to transfer the initial training samples into a higher dimensional feature space, and the best solution is achieved by changing the problem to linear from nonlinear (Feng *et al.*, 2015; Xing *et al.*, 2019) (see Fig. 4). The least-squares learning approach support vector machines (LS-SVM) was used by Pena-Guzmán *et al.* (Peña-Guzmán, Melgarejo and Prats, 2016) to forecast monthly water usage in Bogota, Colombia, for residential, industrial, and commercial sectors. They did so by looking at monthly water use, customer numbers, and prices in the residential, industrial, and commercial sectors. In compliance with national regulations on public services, the city adopts a kind of socioeconomic stratification in which residential properties are grouped into six strata (Benaafi *et al.*, 2022; Tawabini *et al.*, 2022; Yassin *et al.*, 2022).

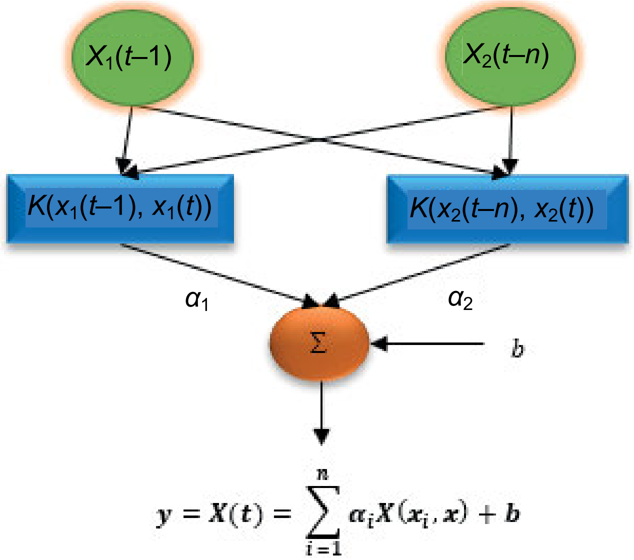

Fig. 4. Structure of support vector machine models; x_1 = first input variable, x_2 = second input variable, $x_1(t{-}1)$ = first input feature or observation at a previous time step $t{-}1$, $x_2(t{-}1)$ = second input feature or observation at a previous time step $t{-}n$, $x_1(t)$ = first input feature or observation at the current time step t, $x_2(t)$ = second input feature or observation at the current time step t, k = kernel function, Σ = summation (or aggregation) node, α_1 = weight parameter for the first kernel box, α_2 = weight parameter for the second kernel box; source: own study

LINEAR AND STATISTICAL METHODS

Multilinear regression (MLR) is a statistical model that determines the relationship between a dependent variable and at least one independent variable. The main purpose of the study by Fullerton, Ceballos and Walke (2016) was to evaluate the dynamics of water demand in the city of El Paso using multiple forecasting approaches (Texas, USA). Gagliardi *et al.* (2017b) introduced a Markov chain (MC) statistical model for forecasting short-term water demand, which provides estimates for future demands as well as the likelihood that the projected demand would fall within the required range. The results suggest that for making short-term projections, the Hamiltonian Monte Carlo (HMC) approach is more exact than the no-U-turn sampler HMC (NHMC) method. Both techniques give probabilistic data on stochastic demand forecast while requiring less computer labour than the majority of current solutions. The ANN and naive Bayes benchmark techniques do not provide this information. After post-processing analysis, it can be derived using more computationally intensive Monte Carlo simulations.

HYBRID METHODS INTEGRATED WITH FILTERS AND EMBEDDED TECHNIQUES

The fundamental variables that influence urban water demand are sometimes difficult to discover using typical algorithms due to the many unknown and difficult to quantify aspects. To address this issue, certain filters, wrappers, and embedded systems may be used. Each has advantages and disadvantages. The mitigation of the recognised curse of dimensionality, lowering the computing cost and gaining a greater interpretation into the primary mechanisms that produced the data are all key elements in optimising forecasting models (Guyon and Elisseeff, 2003; Piramuthu, 2004). It is feasible to develop effective search techniques without losing predictive performance. A number of selection approaches are being developed in order to reduce the computing burden imposed by in-depth searches. Recently, hybrid approaches that combine the advantages of filters and wrappers have been presented (Guyon and Elisseeff, 2003; Hsu, Hsieh and Lu, 2011).

Another field of study is ensemble learning, in which procedures for generating numerous models are applied to forecast a recent scenario. The inspiration behind these techniques may be summarised as the establishment of a prediction model by pooling several methodologies (Dietterich, 2000). When elements with the identical error pattern are merged, there is no additional efficiency, simply an increment in computational effort with no actual performance effects. The establishment of homogeneous ensembles, according to Pinto *et al.* (2014), is the topic of learning with the most literature coverage. Models in homogeneous ensembles are generated using the identical technique. More than one ML method is employed to build heterogeneous ensembles. Because of the varied nature of the fundamental apprentices, it is foreseen that the heterogeneous technique would offer models with higher variation (Webb and Zheng, 2004). According to certain writers, these ensembles outperform homogeneous ensembles (Wichard, Merkwirth and Ogorzalek, 2003). Another approach that is frequently used is one that combines the application of several induction processes together with distinct classes of parameters (Rooney *et al.*, 2004). The best recognised ensemble techniques include Breiman's (1996) bagging (bootstrap aggregating), Freund and Schapire's (1996) boosting, and random forest (Breiman, 2001). Other applications of ensemble in water resources can be found at (Nourani, Elkiran and Abba, 2018; Abba, Nourani and Elkiran, 2019; Elkiran, Nourani and Abba, 2019; Nourani, Elkiran and Abdullahi, 2019; Abba *et al.*, 2020a; Abba *et al.*, 2020b; Abba, Elkiran and Nourani, 2020).

PERFORMANCE CRITERIA

For the development of any model, goodness-of-fit, and error-of-fit, biases are very crucial for evaluating the accuracy and precision of the computing approach. The mean absolute deviation (*MAD*), mean square error (*MSE*), root mean square error (*RMSE*), mean absolute error, coefficient of determination (R^2), and correlation coefficient were used to assess some of the model accuracies. The selection of these characteristics was based on their use in a number of similar research as a reliable way of determining a prediction model's accuracy (Aliyu *et al.*, 2021; Abba *et al.*, 2022; Maroufpoor *et al.*, 2022; Muhammad and Abba, 2023). The *MSE* is the mean squared difference between anticipated and observed values, while the *RMSE* is its square root. The *MSE* and *RMSE* values are always positive, and lower values suggest that the proposed model is more accurate (Ighalo, Adeniyi and Marques, 2020). The R^2 is used to assess a statistical model's adequacy for the provided data. Thus, they provide information regarding how well a model fits the data, and their values range from 0 to 1. Higher values of R^2 indicate a high precision of the developed models (Dashti *et al.*, 2019; Ighalo, Adeniyi and Marques, 2020). Some of these metrics are represented mathematically as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} \left(WD_{\mathrm{obs}_i} - WD_{\mathrm{pred}_i}\right)^2}{N}} \tag{1}$$

$$MAPE = \frac{1}{N}\left(\sum_{i=1}^{N}\left|\frac{WD_{\mathrm{obs}_i} - WD_{\mathrm{pred}_i}}{WD_{\mathrm{obs}_i}}\right|\right) \tag{2}$$

$$MSE = \frac{1}{N}\left(WD_{\mathrm{obs}_i} - WD_{\mathrm{pred}_i}\right) \tag{3}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N} \left(WD_{\mathrm{obs}_i} - WD_{\mathrm{pred}_i}\right)^2}{\sum_{i=1}^{N} \left(WD_{\mathrm{obs}_i} - \overline{WD_{\mathrm{obs}}}\right)^2} \tag{4}$$

$$CC = \frac{\sum_{i=1}^{N}\left(WD_{\mathrm{obs}_i} - \overline{WD_{\mathrm{obs}}}\right)\left(WQI_{\mathrm{pred}_i} - \overline{WD_{\mathrm{pred}}}\right)}{\sqrt{\sum_{i=1}^{N}\left(WD_{\mathrm{obs}_i} - \overline{WD_{\mathrm{obs}}}\right)^2 \sum_{i=1}^{N}\left(WD_{\mathrm{pred}_i} - \overline{WD_{\mathrm{pred}}}\right)^2}} \tag{5}$$

$$MAPE = \frac{1}{N}\sum\nolimits_{i=1}^{N}\left|\frac{WD_{\mathrm{pred}} - WD_{\mathrm{obs}}}{WD_{\mathrm{obs}}}\right|100\% \tag{6}$$

$$MARE = \frac{1}{N}\sum\nolimits_{i=1}^{N}\left|\frac{WD_{\mathrm{pred}} - WD_{\mathrm{obs}}}{WD_{\mathrm{obs}}}\right| \tag{7}$$

where: *WD* = water demand, *CC* = coefficient of correlation, *MAPE* = mean absolute percentage error, *MARE* = mean absolute relative error, WD_{pred}, WD_{obs} = predicted and observed *WD* values, WQI_{pred_i} = predicted water quality index for i^{th} observation, *N* = data point, WD_{obs_i} and WD_{pred_i} = observed and predicted *WD* values for i^{th} observations, $\overline{WD_{\mathrm{obs}}}$ and $\overline{WD_{\mathrm{pred}}}$ = mean of observed and predicted *WD* values, respectively.

DISCUSSION AND FUTURE DIRECTION

It is worth mentioning that the reviewed studies indicated that the soft computing approach has received a lot of attention in the field of water demand modelling. However, a closer look at the broader aspect of AI-based and optimisation models reveals that there are still several gaps that need to be explored to further contribute to the development of water demand modelling. The ANN was the first model to be reviewed in this study, and the outcomes of the literature illustrated that various types of ANN have been employed, such as backpropagation neural network (BPNN), feedforward neural network (FFNN), etc, in water demand forecasting. Other ANNs classification, such as the Elman neural network, radial basis function, and emotional learning, received little attention in this field. For instance, no publication was found on different types of transfer learning ANN comparison or recurrent ANN, and other unsupervised ANN models (Abba, Benaafi and Aljundi, 2023). The most recent advances in the field of neural networks have not been applied to the problem of water demand forecasting. For example, in water demand forecasting, innovative deep learning algorithms that have been demonstrated to be extremely promising in other forecasting fields are still being applied. The number of hidden layers used in ANN, as well as the training processes used, might affect its modelling ability. Choosing the best architecture might be difficult, hence using trial and error methods or a standard approved formular is the best way (Abba *et al.*, 2020c; Abba, Usman and Işik, 2020; Abdullahi, Usman and Abba, 2020; Ghali *et al.*, 2020; Mahmoud *et al.*, 2021). It may be a challenging process, and BPNN or FFNN isn't always the best option, strategy or deliver the finest outcomes.

Only a few studies have looked at other approaches for forecasting, such as a long-term plan. The inability of simple ANN architectures, such as FFNN, to deal with outliers and noisy data, restricting their use to less complicated and linearly inseparable patterns, might be one factor. There are also some patterns in the time series of water demand that need extensive pre-processing. Researchers began developing hybrid approaches based on wavelet and bootstrap coupling to increase prediction accuracy. In addition, the SVM and ANFIS also displayed reasonable attention in the field of water demand and water resources simulation. Most of the studies of ANFIS did not consider the membership functions (MFs) effectively, as we have different MFs that should be used to justify the precision of the models. Recent research demonstrates that individual classical approaches can no longer produce the most accurate results, and that the majority of the dominating methods are produced by using integrated methods. Presenting hybrid models appears to be an attractive field of research in which researchers might increase the accuracy of prediction in water demand forecasting challenges. This study also reviewed different hybrid models and their application in water demand prediction (Mohammed and Ibrahim, 2012; Bakker *et al.*, 2014; Ponte *et al.*, 2016; Zubaidi *et al.*, 2020a; Zubaidi *et al.*, 2020b). Table S1 shows the decades review for water demand modelling and forecasting.

Many of the available data on water consumption are used to build nonlinear forecasting models, and (Nasseri, Moeini and Tabesh, 2011; Ghalehkhondabi *et al.*, 2017) show that models that just utilise proven effective factors are far more accurate than models that take all of the data without taking factor efficacy into account for this type of data. As a result, it's reasonable to assume that the efficacy test will be conducted in future studies before using all of the available data as input to the forecasting model. Another key conclusion of this review research is that no one approach or model delivers the highest forecasting accuracy for all sorts of issues across all categories (AI, hybrid, optimisation, ensemble, and so on). Furthermore, according to some recent study, the generated ANN models produce more accurate forecasts than the other single techniques in the vast majority of circumstances. The ability of ANNs to evaluate non-linear data accounts for this efficiency; however, dealing with non-stationary data remains a hurdle when using ANNs. Consumption, meteorological, and socioeconomic factors were revealed to be used as predictors in calculating ML intelligence techniques in water demand forecasting (Souza Groppo de, Costa and Libânio, 2019). Past consumption patterns, which might range from prior hours to previous years, depending on the study's relevance, are commonly used as consumption variables. Temperature, humidity, snowfall, and rainfall are only a few of the climatic variables that are recorded. The majority of socioeconomic indicators take population, growth rates, and economic considerations into account. Considering the benefits and drawbacks of each accuracy evaluation criterion in relation to the nature of the estimation problem could still be a future research topic, despite the fact that a variety of evaluation criteria were used to determine whether a model had excellent forecasting accuracy or not. The majority of the studies focused on how to develop models using data from a city or nation; however, it looks like effective adaptation with high accuracy for projecting water usage in a smaller region might be an intriguing future study topic. Using data from a larger number of users reduces data noise, making larger datasets simpler to anticipate.

Another motive of this paper is that a detailed examination of water demand in a research region may save money, energy, and time; as a result, modelling methodologies are given a lot of thought when estimating these important characteristics. In poor nations, where the funding for environmental quality assessment and monitoring is lower than in affluent ones, review and modelling procedures are more significant (see Fig. 1). According to the Scopus database's previous reports (1987–2022), there is a lot of interest in water demand modelling considering the applicability of ML models. In Figure 5, the key country clusters (89 countries) as well as the time span covered in the literature are depicted. There were over 1500 keywords included, suggesting the importance of this issue in terms of water demand modelling. The

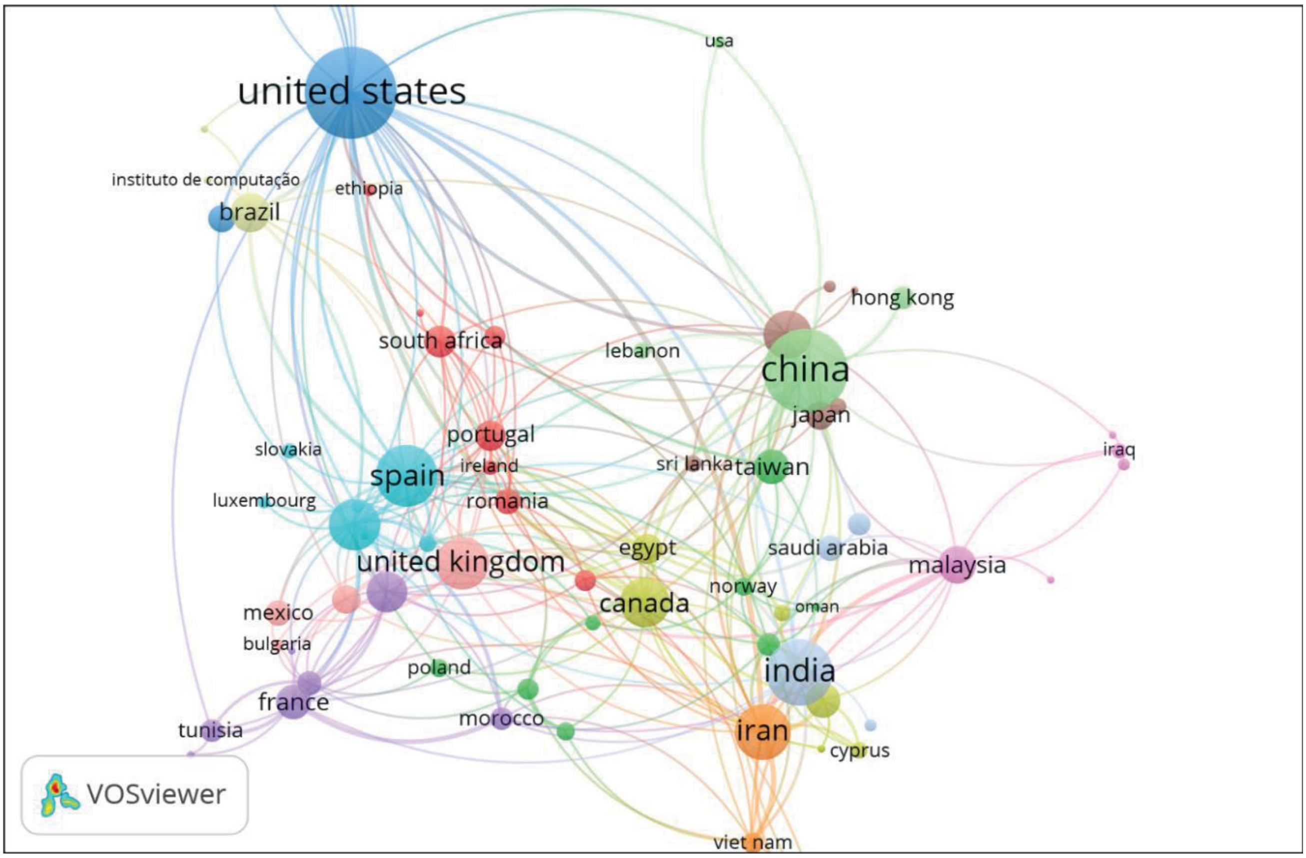

Fig. 5. Investigation of the research region for the water demand forecasting; source: own elaboration using VOSviewer

investigation of new ML models capable of solving engineering challenges is continually ongoing, and academics and scientists are interested in the research subject of predicting water usage using new advanced models.

According to Souza Groppo de, Costa and Libânio (2019), the aim of the paper is to study the water supply system management techniques in order to maintain a balance between supply and demand through operational actions, many of which require the application of forecasting tools. The objective of the paper is to provide an overview of the importance of water demand forecasting and the growing scarcity of water resources, as well as the growing importance of water demand management. And the importance of this paper is that it discusses the optimisation of operations in order to result in substantial savings of 25 to 30% in operating costs, due to the reduction of costs with electricity and treatment inputs. Additionally, the paper examines the numerous factors that affect the demanded water quantity and the most effective combination of technologies for problem-solving, such as fuzzy logic (FL), neural computing (NC), genetic algorithm (GA), evolutionary computation (EC), machine learning (ML), pattern recognition (PR) and computational heuristics (CH). Peng, Wu and Wang (2020) aim to study the cost management of construction water and its characteristics, which include the low and almost constant unit price of water and the huge total amount of water used for construction. The objective of the paper is to analyse the construction water demand, ensure the stability of the water supply during construction, and predict construction water consumption in a scientific and effective way to calculate the cost of construction water and to ensure the stability of the water supply during construction as much as possible. Also, the importance of the paper, based on the authors' findings, was that it highlights the importance of cost management of construction water, which has characteristics such as a low and almost constant unit price of water and a huge total amount of water used for construction. It emphasises the significance of analysing the construction water demand, ensuring the stability of the water supply during construction, and predicting construction water consumption in a scientific and effective way to calculate the cost of construction water and to ensure the stability of the water supply during construction as much as possible.

Shirkoohi, Doghri and Duchesne (2021) aimed to evaluate the application of artificial neural network (ANN) models for short-term (15 min) urban water demand predictions. The objective of the paper is to investigate how the optimisation of the ANN model's hyperparameters with a genetic algorithm (GA) and the use of a growing window approach for training the model could improve the 15-minute predictions. The paper is important as it provides a new approach to predict short-term urban water demand, which can be useful for many real-time control applications such as dynamic pressure control. The authors test the ANN model with a genetic algorithm (GA) and a growing window approach, which helps to optimise the model's hyperparameters, resulting in more accurate predictions. The paper also compares the performance of the ANN model with that of commonly used time series models, namely the autoregressive integrated moving average (ARIMA) model and a pattern-based model, highlighting the superiority of the ANN model. The main aim in paper by Zubaidi *et al.* (2021) was to estimate the stochastic component of urban water demand by using a novel methodology that combines data pre-processing methods, empirical mode decomposition and stepwise regression, and a hybrid model of backtracking search algorithm with an artificial neural network (BSA-ANN). The study aims to improve the accuracy of predictions made in comparison to traditional methods such as time series analysis and regression analysis, and to evaluate the potential of this novel methodology in predicting the monthly stochastic component of water consumption. The main importance of this research is that the author argues that accurate water demand prediction is crucial for proper planning, operation, and development of municipal water systems. They also highlight that Iraq, and specifically the city of Baghdad, is facing challenges related to depleting freshwater resources due to climate change and increasing water demand due to population growth and economic development.

CONCLUSIONS

The purpose of this review was to provide an overview of the water demand forecasting literature published between 2011 and 2021 in order to provide some guidelines, primarily for practicing professionals wishing to implement methods and models appropriate for addressing planning-related decisions that are dependent on future levels of water demand, but it should also be used by researchers seeking to improve predictive models for short, medium, and long-term planning and decisions. There is no worldwide model that outperforms all other models in water demand forecasting at this moment, but each nation has its own model that exceeds others. Another factor to consider is the performance of hybrid models, which is superior to that of classical models. Despite recent major advances in AI technology, no new technique, such as deep neural networks, has emerged as the best prediction model. As a result, water demand forecasting remains a research subject, leaving potential for academics to create hybrid or application-specific approaches.

SUPPLEMENTARY MATERIAL

Supplementary material to this article can be found online at: https://www.jwld.pl/files/Supplementary_material_66_Aminu.pdf.

CONFLICT OF INTERESTS

All authors declare that they have no conflict of interests.

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