SUPPLEMENTARY MATERIAL

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

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Table S1. A decade review of water demand forecasting methods according to the testimonial literature

Author	**Country**	**Evaluation criteria**	**Remark**
Varahrami (2013)	Iran	*RMSE*, *MAE*, *MAPE*	to anticipate short-term water, two types of neural networks, the MLFF and GMDH models, were created; the performance of the created models was assessed using standard statistical criteria; based upon the results obtained and the consequent comparative analysis, it has been found that the GMDH with GA have consistently outperformed the MLFF neural network
Adamowski and Karapataki (2010)	Cyprus	*RMSE*, R^2, *ARE*, *AARE*	a review of the literature on short-term peak water demand forecasting was conducted; LM ANNs are more error-free than CGPB and RP ANNs, as well as MLR, for urban weekly peak water demand
Li and Huicheng (2010)	China	R^2	important elements, such as socioeconomics and climate, were utilised to anticipate urban water demand utilising the HP-MLR and HP-FNN approaches in order to increase precise accuracy; the HP-MLR model was shown to have a high level of predicting accuracy
Nasseri, Moeini and Tabesh (2011)	Iran	R^2, *RMSE*	for estimating water demand in Tehran, a hybrid model combining EKF and GP is created; the sensitivity of the findings for each input is calculated quantitatively for each model; when it came to predicting, the hybrid model was more compatible

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Adamowski *et al*. (2012)	Canada	R^2, *RMSE*, *E*, *RRMSE*	in the city of Montreal, Canada, researchers looked at coupled WA-ANNs for predicting urban water demand on a daily basis throughout the summer season; ANN, MLR, MNLR, and ARIMA were compared to the WA-ANN models; the WA-ANN models were shown to produce more exact findings than the other traditional models
Campisi-Pinto, Adamowski and Oron (2013)	Italy	*RMSE*, *E*, *FSE*	–
Mohammed and Ibrahim (2012)	Iraq	R^2, *RMSE*, *MAPE*	for municipal water demand forecasting, a hybrid wavelet-ANN was created that can combine the DWT approach with the MLP; the study's findings show that the wavelet-ANN model is effective in forecasting daily and monthly municipal water consumption
Ajbar and Ali (2012)	Saudi Arabia	–	in Mecca, Saudi Arabia, a neural network model capable of forecasting water demand in the short and long term was built; the model was shown to be beneficial in terms of simulating both short and long-term transient water use
Yasar, Bilgili and Simsek (2012)	Turkey	*R*, *MAPE*	the water demand in the Turkish city of Adana was predicted using a non-linear regression model; the data was obtained from the Adana metrological station, and the SWR technique was used to pick the "best" regression model
Jia and Hao (2013)	China	*MAPE*, *NMSE*	for improving forecasting accuracy, a hybrid method based on an extreme learning machine model combined with adaptive metrics of inputs is proposed, which can supersede a basic neural network; the results demonstrate that the proposed model is more viable for water demand forecasting and exceeded the other models, which are AR, ANN, SVM, and ELM
Bennett, Stewart and Beal (2013)	Australia	*ARE*, *AAE*, *RMSE*, *MW*, R^2	to anticipate the residential water end-use demand, three conventional ANNs were developed: two feed-forward back propagation networks and one radial basis function network with a sigmoid activation hidden layer and linear activation output layer
Mohammed and Ibrahim (2013)	Iraq	R^2, *RMSE*, *MAPE*	for municipal water demand forecasting, a multilayer perceptron neural network model with multi-activation function known as the MLP-MAF model was developed, which employs a distinct activation function in the hidden layer neuron; this technique is far more accurate and successful than MLP and RBF neural networks, according to the model's success evaluation
Tiwari and Adamowski (2013)	Canada	R^2, *RMSE*, *MAE*	to estimate short-term water demand, a hybrid WBNN was developed; the model's performance was compared to that of ARIMA, ARIMAX, WNN, and BNN models; the hybrid WBNN and WNN models provided much more accurate predicting outcomes in water demand forecasting than the NN, BNN, ARIMA, and ARIMAX models, according to the findings

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Bakker *et al*. (2014)	Netherlands	R^2, *MAPE*, *RE*	when projecting one-day lead water demand, the heuristic model and a transfer/-noise model beat the multiple linear regression model based on six separate models of water demand simulations, but when examining a single model, the heuristic model outperformed the transfer model
Di and Yang **(**2014)	China	–	this study developed a novel way for analysing water resources systems based on dynamical system theory, with GHAGA modelling the unknown factors; it may also be used to examine the supply and demand of water resources in different areas or cities
Emamgholizadeh *et al*. (2014)	Iran	R^2, *RMSE*, *MAE*	two types of ANN specifically MLP/BP and RBF alongside ANFIS, were deployed to determine the DO, BOD and COD parameters for water demand; the performance of the MLP/BP model outperformed ANN-RBF and ANFIS models
Kofinas *et al*. (2014)	Greece	R^2, *RMSE*, *MAE*, *MAPE*	urban water demand pattern for three years' time series, the effort was made for daily, monthly and quarterly values using ARIMA; the only time when the model gave a meaningful value was during the winter's additive; however, one could conclude that it is easier to simulate increasing and decreasing summer demand rather than the winter demand
Tiwari and Adamowski (2015)	Canada	*RMSE*, *MAE*, R^2, *Pdv*	based on the four performance criteria used in the research of urban water demand forecast in situations with finite accessible data, WANN and WBANN models were judged to be significantly superior than ANN and BANN models
Ponte *et al*. (2015)	Spain	*MAPE*	models such as ARIMA, RBF, MLP, ANN were developed to demonstrate the real time water demand forecasting system; the applied MLP turns out to be the most robust method
Ponte *et al*. (2016)	Spain	*MAPE*	time series tests utilising hourly water demand show that the newly built system is more efficient; this demonstrates that the use of AI approaches in the field of water demand forecasting, such as ANNs, may greatly reduce inaccuracy when compared to other older methodologies, lowering WDM costs dramatically
Navarrete-Lòpez *et al*. (2016)	Brazil	–	the SAX was used as an epidemiology-based forecast model where it performed well as a support for approaching visualisation analytics, hence SAX is suitable to work with long term series and is an accurate skeleton for computing resemblance
Peña-Guzmán, Melgarejo and Prats (2016)	Columbia	*AARE*, *RMSE*, R^2	the optimum model for forecasting water demand was determined by comparing the LS-SVM and FNN-BP techniques; according to the performance assessment criteria, the LS-SVM model outperforms the FNN-BP model in terms of properly predicting water demand
Felfelani and Kerachian (2016)	Iran	*MSE*	some ANN models CF-BP, MLP-BP, RBF were developed for the purpose short term prediction of domestic water consumptions under unusual fluctuations in inhabitants; repetitions indicated RBF as the most stable network

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Arandia *et al*. (2016)	Ireland	*RMSE*, *NRMSE*, *MAPE*	SARIMA models were created to anticipate sub-hourly, hourly, and daily water demand; the models were trained using three distinct datasets, and it was discovered that models with weekly seasonality outperform those with daily frequency
Gagliardi *et al*. (2017a)	Italy	*NS*	two short-term water demand forecasting models were developed, both the models performed medium-high, although as the number of users decreases the model's performances declines
Brentan *et al*. (2017)	Brazil	–	there are three methods; SOM, RF, and DMA were created to determine the relationship between water demand, social characteristics, and meteorological data; the obtained findings enable evaluation of the given tools based on SOMs and RF algorithms for their generalisation volume
Boubaker (2017)	Saudi Arabia	*AARE*, *RMSE*, R^2, *MAPE*	in the Hail region of Saudi Arabia, a proposal based on an ARIMA model with PSO as an identification tool was created and applied to the forecast of one-month-ahead municipal water demand; based on the performance assessment criteria, the best PSO-ARIMA run given in this research has indicated that this strategy outperforms BP-FF-ANN, STS-AR, and STS-ARIMA
Gagliardi *et al.* (2017b)	Italy	*NS*	the Markov chain was used to build two short water demand forecasting models, HMC and NHMC; the resultant deterministic projections were compared to those produced by the ANN and nave forecasting models; the results indicated that HMC had greater prediction performance, equal the ANN model's prediction accuracy and exceeding the Nave models
Anele *et al*. (2017)	South Africa	*NS*, *MSE*, *MAPE*, *AIC*	forecasting method for STWD prediction were developed and the performance of AR, MA, ARMA, ARMAX, FFBP-NN were overviewed, the best conditioning options for assessing the predictive probability distribution of future needs are ARMA and ARMAX, according to a comparative analysis of forecasting models
Vijai and Bagavathi Sivakumar (2018)	India	*MSE*, *RMSE*, R^2, *MAE*	the methods of ANN, DNN, ELM, LSSVM, GPR, RF, and MR were used to anticipate water demand; each technique's performance has been compared using the performance Metrix; the forecast was produced for intervals of 1, 12, and 24 hours, and the ANN model performed best
Duarte Alonso and Kok (2018)	Australia	*RMSE*, *MSE*, *MAE*	water utilities, stakeholders, and policymakers need to be able to accurately estimate municipal water demand; the SSA and hybrid PSO-ANN models were constructed, with the hybrid PSO-ANN outperforming the SSA; the study advises water corporations to use the hybrid PSO-ANN approach to forecast water demand in a variety of conditions and locales

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Seo, Kwon and Choi (2018)	South Korea	*MAE*, *RMSE*, *R4MS4E*, *MdAPE*, *MARE*, *MIOA*, *MCE*	the decomposition and prediction of water demand time series were examined using a VMD-based water demand forecasting model, while ANN and ELM were constructed for the decomposition and prediction of water demand time series; the ELM outperforms the other models for single forecasting models, whereas the combination of VMD-ELM produces the best presentation of all the models
Zubaidi *et al*. (2018)	Australia	*MAE*, *MAPE*, *MSE*, *RMSE*	to choose the optimal model input, many statistical models, including hybrid GSA-ANN and BSA-ANN, were used; in terms of water demand forecast accuracy, the GSA-ANN model outperforms the other hybrid model in this study
Oyebode (2019)	South Africa	*RMSE*, R^2, *NSE*	the study looked at five feature selection approaches for selecting the best subset of features for a water demand forecasting model, and they were compared to a baseline scenario with eight possible explanatory factors and six scenarios, the lowest and maximum temperatures, as well as the HDI, were chosen, together with the population and number of home connections, which are commonly employed in water demand predictions
Souza Groppo de, Costa and Libânio (2019)	Brazil	–	a thorough examination of urban water demand forecast using artificial intelligence was conducted in order to offer advice to sanitation specialists on methodologies and models; this research reveals that the bulk of studies are primarily concerned with work system management; as a result, long-term projections and predictions in the domain of water consumption are possible
Oyebode and Ighravwe (2019)	South Africa	*RMSE*, R^2, *MAPE*	to forecast water demand, ML approaches, such as ANN–CG, ANN–DE, and SVM, were combined with ES and MLR; during the study of the scenarios, it was discovered that the ANN–DE model performed better than the other prediction models; the performance was in the following order: ANN–DE > SVM > MLR > ANN–CG; the findings of this investigation show that the ANN–DE model outperformed the ES results of a typical time series model
Xu *et al*. (2019)	China	*NRMSE*, R^2, *MAPE*	the CDBESN model was created to forecast real-time urban water consumption; a CDBN-based feature extraction model and an ESN-based regression model were combined to create the model; the ESN, CDBNN, and SVR models were then compared to the CDBESN model; and the end results indicated that it outperformed the other models significantly
Donyaii, Sarraf and Ahmadi (2020)	Iran	–	to enhance the procedure of the Boostan dam reservoir, a novel hybrid whale optimisation differential evolution algorithm was proposed; this was an improved version of the whale optimisation, and thus the convergence rate, performance, and statistical parameters of the three algorithms were improved by a factor of ten
Peng, Wu and Wang (2020)	China	R^2, *MAE*, *RMSE*	to estimate water consumption at a construction site, a BP neural network enhanced via particle swarm optimisation was constructed and compared to a standard BP neural network, the enhanced model, on the other hand, outperformed the BP algorithm

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Zubaidi *et al*. (2020b)	South Africa	*RMSE*, *MAE*, *MA*, *CE*	in South Africa, unique combination models incorporating pre-treatment signal, mutual information, and the BSA-ANN approach were evaluated to calculate the monthly municipal water needed based on prior water usage; the BSA-ANN model, on the other hand, produced the best results; furthermore, based on the performance assessment criteria, it demonstrated to be more reliable than the CSA-ANN
Zubaidi *et al*. (2020a)	Australia	*MAE*, *MSE*, *MARE*, R^2	a study was conducted into data pre-processing and automatic machine learning based on a variety of environmental parameters; based on the performance criteria, the SMA-ANN algorithm was shown to be superior to both the BSA-ANN and MVO-ANN algorithms
Menapace, Zanfei and Righetti (2021)	Italy	*MARE*, R^2	in-depth study about the tuning of ANN structure using the four states of art of ANN was carried out which are FFNN, LSTM, SRNN, GRU; the tuning of LTSM and GRU provide the best performing models with the lowest variability among models
Shirkoohi, Doghri and Duchesne (2021)	Canada	*RRMSE*, *MAPE*, *E*	the use of (ANN) models for short-term (15 min) urban water demand forecasting was determined, the ANN model was linked with a GA, and then the ARIMA model and a pattern basis model were evaluated; other conventional models were outperformed by the GA optimised ANN model
Zubaidi *et al*. (2021)	Iraq	*MAE*, *MARE*, *CE*	for a city in Iraq, a novel approach was created to anticipate the stochastic component of urban water demand; EMD is a technique used in the approach to identify the optimal scenarios for independent variables; the findings show that data EMD is capable of detecting the stochastic signal in water data and selecting the optimal model input scenario
Kofinas *et al*. (2014)	China	*MAE*, *RMSE*, *NSE*	for the first time, OD, CMIF, and CEEMDAN have been introduced to water demand forecasting; the results were then compared with those of ANN and SVR to investigate the efficiency of the developed models; despite the higher computational load, the developed models performed better than the ANN and SVR-based models

Explanations: *RMSE* = root mean square error, *MAE* = mean absolute error, *MAPE* = mean absolute percentage error, R^2 = coefficient of determination, *ARE* = absolute relative error, *AARE* = average absolute relative error, *E* = efficiency index, *RRMSE* = relative root mean square error, *FSE* = final simulation error, *R* = correlation coefficient (Pearson's *R*), *NMSE* = normalised mean square error, *AAE* = average absolute error, *MW* = mean weighted error, *MSE* = mean square error, *NS* index = Nash–Sutcliffe index, *RE* = relative error, *Pdv* = predictive deviation value, *NRMSE* = normalised root mean square error, *NS* = Nash–Sutcliffe efficiency, *AIC* = akaike information criterion, *R4MS4E* = fourth-root mean fourth-power error, *MdAPE* = median absolute percentage error, *MARE* = mean absolute relative error, *MIOA* = model input–output accuracy, *MCE* = model comparison error, *NSE* = Nash–Sutcliffe efficiency coefficient, *MA* = moving average, *CE* = coefficient of efficiency, MLFF = multi-layer feedforward network, GMDH = group method of data handling, GA = genetic algorithm, LM ANN = Levenberg–Marquardt artificial neural network, CGPB = conjugate gradient with Powell–Beale restarts, RP ANN = resilient propagation artificial neural network, MLR = multiple linear regression, HP-MLR = high-performance multiple linear regression, HP-FNN = high-performance feedforward neural network, EKF = extended Kalman filter, GP = genetic programming, WA-ANN = wavelet-artificial neural network, MNLR =

multinomial logistic regression, ARIMA = autoregressive integrated moving average, DWT = discrete wavelet transform, MLP = multilayer perceptron, SWR = stepwise regression, AR = autoregressive model, ANN = artificial neural network, SVM = support vector machine, ELM = extreme learning machine, MAF = moving average filter, RBF = radial basis function, WANN = wavelet artificial neural network, WBANN = wavelet–bootstrap artificial neural network, WBNN = wavelet–bootstrap neural network, ARIMAX = autoregressive integrated moving average with exogenous inputs, WNN = wavelet neural network, BNN = Bayesian neural network, NN = neural network, BANN = bootstrap artificial neural network, AI = artificial intelligence, WDF = wavelet decomposition framework, EANN = evolutionary artificial neural network, WDM = wavelet decomposition method, SAX = symbolic aggregate approximation, LS-SVM = least squares support vector machine, FNN-BP = feedforward neural network with backpropagation, CF-BP = conjugate function backpropagation, MLP-BP = multilayer perceptron with backpropagation, GHAGA = genetic hybrid adaptive genetic algorithm, ANFIS = adaptive neuro-fuzzy inference system, DO = dissolved oxygen, BOD = biochemical oxygen demand, COD = chemical oxygen demand, SOM = self-organising map, RF = random forest, DMA = dynamic mode averaging, PSO = particle swarm optimisation, BP-FF-ANN = backpropagation feedforward artificial neural network, STS-AR = space-time series autoregressive, STS-ARIMA = space-time series autoregressive integrated moving average, HMC = hidden Markov chain, NHMC = non-homogeneous Markov chain, STWD = short-time wavelet decomposition, ARMA = autoregressive moving average, ARMAX = autoregressive moving average with exogenous variables, FFBP-NN = feedforward backpropagation neural network, DNN = deep neural network, LSSVM = least squares support vector machine, GPR = Gaussian process regression, MR = multiple regression, SSA = singular spectrum analysis, PSO-ANN = particle swarm optimisation – artificial neural network, VMD-ELM = variational mode decomposition – extreme learning machine, VMD = variational mode decomposition, GSA-ANN = gravitational search algorithm – artificial neural network, BSA-ANN = backtracking search algorithm–artificial neural network, HDI = human development index, ML = machine learning, ANN–CG = artificial neural network trained with conjugate gradient, ANN–DE = artificial neural network trained with differential evolution, ES = evolution strategy, CDBESN = convolutional deep belief echo state network, CDBN = convolutional deep belief network, ESN = echo state network, CDBNN = convolutional deep Bayesian neural network, SVR = support vector regression, BP = backpropagation, CSA-ANN = cuckoo search algorithm – artificial neural network, SMA-ANN = sine cosine metaheuristic algorithm–artificial neural network, MVO-ANN = multi-verse optimiser – artificial neural network, GEP = gene expression programming, FFNN = feedforward neural network, LSTM = long short-term memory, SRNN = simple recurrent neural network, GRU = gated recurrent unit, EMD = empirical mode decomposition, OD = oxygen demand, CMIF = combined mutual information function, CEEMDAN = complete ensemble empirical mode decomposition with adaptive noise.

Source: own elaboration based on literature.

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