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Assessing the Benefits of Nature-Inspired Algorithms for the Parameterisation of ANN in the Prediction of Water Demand

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Abstract

Accurate forecasting techniques for a stochastic pattern of water demand are essential for any city that faces high variability in climate factors and a shortage of water resources. This is the first research that assesses the impact of climatic factors on urban water demand in Iraq, which is one of the hottest countries in the world. We present a novel forecasting methodology that includes data preprocessing and an artificial neural network (ANN) model, which is integrated by a recently nature-inspired metaheuristic algorithm (marine predators algorithm (MPA)). The

MPA-ANN algorithm will be compared with four different nature-inspired metaheuristic algorithms. Nine climatic factors were examined with different scenarios to simulate the monthly stochastic urban water demand over eleven years for Baghdad City, Iraq. The results reveal that: 1) precipitation, solar radiation, and dew point temperature are the most relevant factors to develop the models. 2) The ANN model becomes more accurate when it is used in combination with the MPA. 3) This methodology can accurately forecast the water demand considering the variability in climatic factors. These findings are of considerable significance to water utilities to plan, review, and compare the availability of freshwater resources and increase water requests (i.e., adaptation variability of climatic factors).

Keywords: Baghdad City; climatic factors; machine learning; metaheuristic algorithm; water demand model.

Introduction

Secure clean water availability, quantity and quality, for all inhabitants under the variability of climate change is fundamental to get a resilient environment in modern cities (Tortajada et al. 2019). Freshwater scarcity has appeared as a global challenge because of the impact of climate change and socio-economic factors. The water scarcity led to an imbalance between water delivered and demand. Worldwide, more than one billion individuals have lack access to safe potable water (Ahmadi et al. 2020).

Several studies conducted in different areas have shown that the magnitude and pattern of precipitation differ as a result of climate change (Szeląg et al. 2021). The high variability of climate change imposes an increasing challenge for the management of freshwater resources (i.e., due to the reduction of freshwater availability) (Nunes Carvalho et al. 2021), which highlights the increasing need for protecting the quantity and quality of water resources particularly in sensitive zones (Lama et al. 2021). Management of municipal water planning considering a nuanced quantitative understanding of water needed is fundamental for solving the issue of water security (Capt et al. 2021). Accordingly, forecasting municipal water consumption in the future with greater precision is essential when designing water distribution networks (Pandey et al. 2021).

Iraq is located in the fastest-warming area of the world, the temperature reaches 54 °C that is considered one of the hottest ever measured in the Eastern Hemisphere (Salman et al. 2018). Iraq depends on Tigris and Euphrates Rivers as a primary freshwater resource, where they originate outside the Iraqi borders from Turkey. The discharge rate of these rivers has reduced to less than a third of their normal capacity because of the water policies in Turkey, Iran, and Syria. Moreover, investments in industries after 2003 (e.g., the oil industry) led to increased water consumption (Osman et al. 2017). In addition, different research studies have been conducted to assess the quality of freshwater in Iraq and reported an increase in the occurrence of several contaminants (Ewaid et al. 2018). Based on the above-mentioned problems coupled with others such as continuing wars, embargo, and terrorism led to an unclear view of the decision-maker to manage the water resources under its decrease in availability.

Estimating in advance the municipal water demand is crucial to enhance municipal water security, and monthly estimation is vital to manage dam reservoirs (Ebrahim Banihabib and Mousavi-Mirkalaei 2019). Accurate forecasting of municipal water demand will help utilities to recognise the temporal patterns of water needed to satisfy the balance between water delivered and ordered, which in turn supports the sustainability of the water system (Altunkaynak and Nigussie 2017).

De Souza Groppo et al. (2019) and Ghalehkhondabi et al. (2017) reported that forecasting of municipal water consumption progressed over the last several decades, focusing on different forms of machine learning techniques and the artificial neural network (ANN) as the most popular techniques. Xenochristou and Kapelan (2020) stated that ANN models have been applied in different research and have been proven to be effective in forecasting short-, medium-, and long-term urban water demand (Bata et al. 2020; Tiwari and Adamowski 2015; Zubaidi et al. 2020). Also, it was successfully used in eco-hydraulic and environmental engineering (Lama et al. 2021; Pandya et al. 2017; Sadeghifar et al. 2022; Zhu et al. 2022). But determining the optimum hyperparameters of the machine learning models is still considered a substantial challenge. To address this, automated machine learning approaches (such as AutoML) have been proposed to help build hybrid prediction models (He et al. 2021) without extensive knowledge of statistics and machine learning (Zöller and Huber 2021), while reducing human effort and potential bias (Hutter et al. 2019). In addition, recent studies (Archetti and Candelieri 2019; Chatzipavlis et al. 2018; Frazier 2018) have investigated the use of Bayesian Optimization (BO) to identify an optimal configuration of the hyperparameters of a machine learning algorithm within a limited number of trials, especially for long-term data. Although several automated machine learning approaches have been applied in the last decades in the area of forecasting water demand, there is still room for improvement (De Souza Groppo et al. 2019). For example, Candelieri and Archetti (2018) reported a substantial improvement in forecast precision regarding previous research studies (Candelieri 2017; Shabani et al. 2018). Furthermore, Candelieri and Archetti (2018) intend to utilise the extra forecast method in other application fields. These research studies highlight the importance of continuing the investigation of the use of new methodologies, which may offer scientific and useful insights to policymakers. Also, based on recent literature (Archetti and Candelieri 2019; Chatzipavlis et al. 2018; Frazier 2018), Bayesian Optimization (BO) can identify an optimal configuration of the hyperparameters of a machine learning algorithm within a limited number of trials, especially for long-term data.

Therefore, in this research, five nature-inspired optimisation algorithms will be used to integrate the ANN model to simulate monthly stochastic water demand data. These algorithms include: 1) Slime mould algorithm (SMA), which was proposed by Li et al. (2020) and successfully applied in feature selection (Abdel-Basset et al. 2021), wind power prediction (Yan and Wu 2020), and image segmentation problem (Abdel-Basset et al. 2020); 2) Marine predators algorithm (MPA) that was proposed by Faramarzi et al. (2020) and effectively applied in COVID-19 detection model (Abdel-Basset et al. 2020), engineering applications (Ghafil and Jármai 2020), and tensile behaviour prediction (Abd Elaziz et al. 2020); 3) Multi-verse optimiser (MVO) that was efficiently utilised in solving engineering optimisation issues (Sulaiman et al. 2020), streamflow prediction modelling (Mohammadi et al. 2020), and design optimisation of a cam-follower mechanism (Abderazek et al. 2020); 4) Backtracking search algorithm (BSA), which was successfully used in finding soil parameters (Jin and Yin 2020), parameter estimation of power signals (Mehmood et al. 2020), and optimisation of photovoltaic models (Zhang et al. 2020); 5) Crow search algorithm (CSA) that was effectively applied in feature selection (Ouadfel and Abd Elaziz 2020), reinforced concrete (Sultana et al. 2020), and solving optimal control issues (Turgut et al. 2020).

Currently, urban water demand forecasting is extremely challenging for water companies that are struggling for adapting water systems specifically in terms of increasing concerns about the impact of climate change and water security. Additionally, there are very limited research studies about forecasting the stochastic signal of water needed, based on climatic factors. Consequently, considerable uncertainty still exists concerning the unexpected growth of stochastic patterns in water demand resulting from the stochastic impact of climatic factors (Zubaidi et al. 2018; Zubaidi et al. 2020). Based on the literature review, the innovation of this research is to i) Assess, for the first time in Iraq, to what extent climatic factors have driven the urban water demand. ii) Integrate the ANN model with the recently MPA algorithm (MPA-

ANN), which is the first application in the field of urban water demand forecasting. iii) Compare the MPA-ANN algorithm with four nature-inspired optimisation algorithms (SMA, MVO, BSA, and CSA) to increase the forecasting range and decrease the uncertainty. iv) Apply a novel methodology (data pre-processing and hybrid model) to forecast the monthly stochastic pattern of water demand. v) Offer a scientific view to decision-makers about the impact of climatic factors on water demand to satisfy sustainability in a country that faces a unique environment of climate change and water scarcity.

Study area

Iraq is one of the Arab countries that is located in an arid to a semi-arid area in the Middle East and its capital is Baghdad City, which is situated in the centre of Iraq, covering an area of around 204.2 km^2 (Fig. S1). Baghdad City suffered from sectarian violence from 2004 to 2017 that impacted the pattern and population growth rate of the city. However, Iraq had a rapid population growth rate of 2.5% in 2018 with more than 8.5 million inhabitants living in Baghdad. The Mayoralty of Baghdad City has ten water treatment projects to treat and deliver potable water from the Tigris River to various customer sectors (residential, institutional, industrial, and commercial). The predominant climate in Iraq is dry and hot to extremely hot in summer, and cold and wet in winter. Iraq faces considerable climate change that causes extreme heat waves (i.e., increase temperature degrees) and decreases the magnitude and change pattern of precipitation. Hence, the capacity of freshwater resources reduced, and the municipal water system became under stress (Chabuk et al. 2020; Ewaid et al. 2018; Zubaidi et al. 2019).

Methodology

The urban water demand methodology suggested here allows medium-term time-series demand forecasting to be calculated based on climatic factors. Fig. 1 shows the steps needed to build the water forecast methodology.

Data of forecast model

Historical data can assist to estimate and extrapolate possible impacts in the future, and the forecast will contribute to building a looked-for future (Partidário 2007). Development of the urban water demand-forecast model necessitates the availability of historical water consumption and climatic factors time series data. Accordingly, in this study, nine climatic factors are used to simulate the monthly municipal water demand (million cubic metres, MCUM) over eleven years (2003-2013) in Baghdad City, Iraq. These climatic factors were used effectively to forecast water demand with different scenarios in several previous studies in different regions. It includes maximum temperature (T_{max}) ($^{\circ}C$), minimum temperature (T_{min}) ($^{\circ}C$), mean temperature (T_{mean}) ($^{\circ}C$), precipitation (P) (mm), wind (W) (m/s), solar radiation (S_{rad}) (MJ/m^2), relative humidity (RH) (%), dew point temperature (T_{dp}) ($^{\circ}C$), surface pressure (S_p) (kPa).

The socio-economic factors (*e.g.*, population) are deterministic components (Rasifaghihi et al. 2020; Zubaidi et al. 2020). Therefore, it is out of scope because this study focuses on the impact of climatic factors, which have stochastic behaviour on water consumption.

Data Preprocessing

Data preprocessing is a substantial phase that brings the data to such a state to enable the developed model to easily and accurately forecast the available data. It can be divided into three parts include normalisation, cleaning, and choice of best model input (Tabachnick and

Fidell 2013). Haque et al. (2018) claimed that time series should be scaled down (normalised) to make the output space smoother and reduce the impact of outliers, and Cleophas and Zwinderman (2016) suggested applying natural logarithm to normalise the time series.

Data cleaning means decomposing the time series trend, seasonal (non-stationary components), stochastic (stationary component), and noise. After that, select the stochastic component only for dependent and independent factors because of the stochastic relationship between climatic factors and water consumption (Zubaidi et al. 2020). So, the pre-treatment signal approach will be used to implement this step.

The main aim of a factor choice procedure is to find the right independent factors, which have a significant effect on the dependent factor and could yield a robust forecast model (Seo et al. 2018). In this research, the tolerance technique will be used to select the model input factors by avoiding multicollinearity. Each independent factor in the best scenario should have a tolerance coefficient of more than 0.2 to ensure that there is no collinearity (Cleophas and Zwinderman 2016).

Artificial neural network (ANN)

ANN is currently the most common machine learning technique applied in the hydrological area, in particular, learning using a feedforward backpropagation (*FFBP*) structure. The *FFBP* is used in precisely simulating municipal water needed across various spatiotemporal scales due to its ability to map the non-linear behaviour (i.e., trend and seasonal) of water data (Shirkoohi et al. 2021; Zounemat-Kermani et al. 2020).

The Levenberg–Marquardt (*LM*) algorithm was used to train the ANN approach due to its the most suitable algorithms known to minimise the error of the prediction model as well as its capability to efficiently simulate any predictor/response map (Bayatvarkeshi et al. 2018; Zare

Abyaneh et al. 2016). As in Zubaidi et al. (2020), the topology of the ANN can be classified into four layers of neurons including the input layer which contains the predictor factors (i.e., climatic factors), two hidden layers, and the output layer which contains the response factors (i.e., water demand) (Fig. S2). Additionally, the tansigmoidal activation function was chosen in the first and second hidden layers, whilst the linear activation function was employed in the output layer. The process of ANN training was repeated many times over an epoch (i.e., 1000 iterations) until the error between the actual and simulated urban water time series data reaches its minimum. In this study, for each variable, 70% (92 out of 132) of the dataset was utilised for training, 15% (20 out of 132) as test set, and 15% (20 out of 132) for validation. Choosing these percentages of training, test, and validation datasets follow several earlier studies, e.g., (Chyad et al. 2022; Zubaidi et al. 2020; Zubaidi et al. 2020).

Indeed, the ANN performance relies on the optimisation of its hyperparameters that define the options of topology and learning of ANN. Recently, ANN models were successfully integrated by various metaheuristic algorithms to select the best values of ANN's hyperparameters for short- and long-term. However, these combined techniques were applied in a limited number in the urban water demand field and additional research effort is required to enhance more effective and precise combined models in the future (Shirkoohi et al. 2021; Zounemat-Kermani et al. 2020).

In this study, the ANN model will be combined with the MPA algorithm to select the learning rate (*Lr*) and the number of neurons hidden (*N1* and *N2*) for the first and second hidden layers instead of the trial-and-error approach. The MPA-ANN algorithm will be compared with SMA-ANN, CSA-ANN, BSA-ANN, and MVO-ANN to increase the forecasting range and decrease the uncertainty.

Marine predators algorithm (MPA)

The marine predator algorithm (MPA) is a novel metaheuristic optimization algorithm in which the behaviour of ocean creatures in their search for food is emulated. These creatures include sharks, monitor lizards, sunfish, equine fishes, and swordfish. In the ocean, both predators and prey strive to get their food to survive. This behaviour inspires researchers to follow this approach to get a sound algorithm in terms of its fitness. Formulation of MPA should begin by assigning an initial random set of solutions based on the search space as an initial step as illustrated in Eq. 1:

$$Z = \boldsymbol{X}_{\boldsymbol{lower}} + rand * \left(\boldsymbol{X}_{\boldsymbol{upper}} - \boldsymbol{X}_{\boldsymbol{lower}}\right) \tag{1}$$

Where:

$\boldsymbol{X}_{\boldsymbol{lower}}\ and\ \boldsymbol{X}_{\boldsymbol{upper}}$ are the lower and upper bond of search space, respectively, $rand$ is a random number with a range of [0, 1].

Two matrices must be defined in MPA because of the nature of the algorithm in which both predator and prey are looking for their own food. Therefore, both are considered search agents. These two matrices are referred to as elite (for predator) and prey matrices, respectively as shown in Eq. 2 and 3. According to the concept of the “survival of the fittest”, the top predators should be the ones with higher hunting kills and merits in the search space. As such, the Elite matrix should only include the fittest agents in the search space (predators). Then, depending on the prey positions, the Elite matrix will be updated. Regarding the Prey matrix, the dimensions of this matrix must be the same as for the Elite matrix. In this matrix, the predator updates its position based on this matrix.

$$\boldsymbol{Elite} = \begin{bmatrix} \boldsymbol{X_{11}^1} & \boldsymbol{X_{12}^1} & \vdots & \boldsymbol{X_{1d}^1} \\ \boldsymbol{X_{21}^1} & \boldsymbol{X_{22}^1} & \vdots & \boldsymbol{X_{2d}^1} \\ . & . & . & . \\ . & . & \vdots & . \\ \boldsymbol{X_{n1}^1} & \boldsymbol{X_{n2}^1} & & \boldsymbol{X_{nd}^1} \end{bmatrix} \tag{2}$$

$$\boldsymbol{Prey} = \begin{bmatrix} \boldsymbol{X_{11}} & \boldsymbol{X_{12}} & . & \boldsymbol{X_{1d}} \\ \boldsymbol{X_{21}} & \boldsymbol{X_{22}} & . & \boldsymbol{X_{2d}} \\ . & . & . & . \\ \boldsymbol{X_{n1}} & \boldsymbol{X_{n2}} & . & \boldsymbol{X_{nd}} \end{bmatrix} \tag{3}$$

where $\boldsymbol{X_1^1}$ represents the optimal predator vector, *n* is the number of search agents, and *d* is the number of dimensions.

In the two matrices, the positions of the predators and preys are updated according to three phases. These phases are merely dependent on the velocity difference between predator and prey. To emulate the whole life of both predator and prey in nature, a designated number of iterations should be assigned in each phase. The details of each phase will be discussed in the subsections below.

Phase 1: High-velocity ratio

In this phase, the movement of the predator is faster than the prey. This phase occurs in one-third of the total number of iterations (i.e., $\frac{1}{3}t_{max}$). The step size of prey movement is updated as in the equation below:

$$S_i = \boldsymbol{R_B} \otimes (\boldsymbol{Elite_i} - \boldsymbol{R_B} \otimes \boldsymbol{Prey_i}), \qquad i = 1,2,\dots,n \tag{4}$$

$$\boldsymbol{Prey_i} = \boldsymbol{Prey_i} + P.\boldsymbol{R} \otimes S_i \tag{5}$$

Where $\boldsymbol{R}$ is a random vector with a range of [0, 1], P = 0.5 a constant number, $\boldsymbol{R_B}$ is a random vector referring to Brownian motion, $\otimes$ refers to element-wise multiplication process.

Phase 2: Unit velocity ratio

In this phase, the predator and prey are moving at the same pace. The prey movement is represented by Levy flight while the predator is represented by Brownian motion. This phase occurs in the second third of the total iterations (i.e., $\frac{1}{3}t_{max} < t < \frac{2}{3}t_{max}$). The following equations are applied to the first half of the population.

$$S_i = R_L \otimes (\boldsymbol{Elite_i} - R_L \otimes \boldsymbol{Prey_i}), \qquad i = 1,2,\dots,n \tag{6}$$

$$\boldsymbol{Prey_i} = \boldsymbol{Prey_i} + P.\boldsymbol{R} \otimes S_i \tag{7}$$

Where R_L represents numbers following Levey distribution. The second half of the population is subjected to the following equations:

$$S_i = \boldsymbol{R_B} \otimes (\boldsymbol{R_B} \otimes \boldsymbol{Elite_i} - \boldsymbol{Prey}_i), \qquad i = 1,2,\dots,n \tag{8}$$

$$\boldsymbol{Prey_i} = \boldsymbol{Prey_i} + P.CF \otimes S_i \, , CF = \left(1 - \frac{t}{t_{max}}\right)^{2\left(\frac{t}{t_{max}}\right)} \tag{9}$$

CF represents a parameter that controls the movement step size of the predator.

Phase 3: Low-velocity ratio

This is the last phase of the optimization and it simulates predator movements when it is faster than the prey. It occurs in the last third of the total iterations (i.e., $\frac{2}{3}t_{max}$)

$$S_i = R_L \otimes (R_L \otimes \boldsymbol{Elite_i} - \boldsymbol{Prey_i}), \qquad i = 1,2,\dots,n \tag{10}$$

$$\boldsymbol{Prey_i} = \boldsymbol{Prey_i} + P.CF \otimes S_i \, , CF = \left(1 - \frac{t}{t_{max}}\right)^{2\left(\frac{t}{t_{max}}\right)} \tag{11}$$

The detailed information of both motions (Levy and Brownian) will be furtherly discussed in subsections below:

Brownian motion: this motion is inspired by the normal distribution with a mean of zero ($\mu = 0$) and a variance of one ($\sigma^2 = 1$). To determine the Probability Density Function (*PDF*) corresponding to this motion at point x, the following formula should be used:

$$P_B(x,\mu,\sigma)=\frac{1}{\sqrt{2\pi\sigma^2}}\exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)=\frac{1}{\sqrt{2\pi}}\exp\left(\frac{x^2}{2}\right) \quad (12)$$

Levy flight: this is a stochastic and random step size in which Levy distribution is followed. The probability function of Levy distribution is formulated as:

$$L\left(x_j\right)\approx\left|x_j\right|^{1-\alpha} \quad (13)$$

where x_j is the flight length, and α is the exponent of the power-law that has a range (1,2). The probability density of the Levy distribution is formulated as:

$$P_L(x,\mu,\sigma)=\frac{1}{\pi}\int_0^\infty \exp\left(-\gamma q^\alpha\right)\cos\left(qx\right)dq \quad (14)$$

where γ is the scale unit. The integral form can be used if α falls within its normal range (1, 2). As such, a Gaussian distribution is obtained if α equals 2 while Cauchy distribution can be obtained if α is 1. Higher values of x require series of expansion method as shown:

$$P_L(x,\mu,\sigma)=\frac{\gamma\Gamma\left(1+\alpha\right)\sin\left(\frac{\pi\alpha}{2}\right)}{\pi x^{(1+\alpha)}}, x=\infty \quad (15)$$

where Γ is a gamma function in which $\Gamma(1+\alpha)$ equals to α!. Herein, α ranges from 0.3 to 1.99. The present study follows Levy distribution to generate a random number as written below:

$$Levy\left(\alpha\right)=0.05\times\frac{x}{|y|^{\left(1/\alpha\right)}} \quad (16)$$

where y and x are two variables with normal distribution as follows:

$x = Normal(0, \sigma_x^2)$ and $y = Normal(0, \sigma_y^2)$ where σ^2 can be determined as:

$$\sigma_x = \left[\frac{\Gamma(1+\alpha)\, n\left(\frac{\pi\alpha}{2}\right)}{\Gamma\left(\frac{(1+\alpha)}{2}\right)\alpha 2^{\left(\frac{\alpha-1}{2}\right)}} \right]^{1/\alpha} \tag{17}$$

where, $\sigma_y = 1$and $\alpha = 1.5$.

Eddy formation and effect of FAD

It should be noted that in formulating MPA, the surrounding environment can play a vital role in terms of its impacts on the behaviour of prey, specifically, the eddy formulation and fish aggregating devices (*FADs*). This effect can be presented as:

$$\boldsymbol{Prey_i} = \begin{cases} \boldsymbol{Prey_i} + CF[\boldsymbol{X_{min}} + \boldsymbol{R} \otimes (\boldsymbol{X_{max}} - \boldsymbol{X_{min}})] \otimes \boldsymbol{\bar{U}} & if\ \boldsymbol{r} < FAD \\ \boldsymbol{Prey_i} + [FADs(1-\boldsymbol{r}) + \boldsymbol{r}](\boldsymbol{Prey_{r1}} - \boldsymbol{Prey_{r2}}) & if\ \boldsymbol{r} > FAD \end{cases} \tag{18}$$

Where ***r*** is a random value in a range of zero to 1. ***r***1 and ***r****2* refer to the random indices of prey matrix. *FADs* = 0.2 denotes the probability of *FADs* effect. The $\boldsymbol{\bar{U}}$ is a binary vector. $\boldsymbol{X_{max}}, \boldsymbol{X_{min}}$ are vectors of lower and upper bounds of the dimensions.

In the MPA technique, a memory saving should be done so that the old position of the prey can be saved to compare the fitness values pertaining to the old position of prey with other successive solutions in which prey update their positions during the simulation process. The flowchart of the MPA-ANN algorithm is presented in Fig. S3.

Performance evaluation criteria

The parameters of statistical criteria indicate the accuracy of measuring prediction, so forecast error plays a significant role in the choice of an appropriate model that diminishes deviations in future forecasts (Donkor et al. 2014). It is essential to select the criteria that are proper for a particular application due to the lack of global performance criteria (Seo et al. 2018). In this study, different performance criteria were considered for assessing the performance of the model. These criteria include the coefficient of determination (R^2), coefficient of efficiency (*CE*), nash–sutcliffe index (*NSI*), root mean square error (*RMSE*), mean absolute error (*MAE*), and mean bias error (*MBE*). The forecast technique has good accuracy and high performance to simulate the water advance time when satisfying one of these values of R^2, *CE* more than 0.9, or the values of *RMSE*, *MAE*, and *MBE* approach to zero (Dawson et al. 2007; Li et al. 2013), as well as if the value of *NSI* approaches to one (Jain and Sudheer 2008).

Augmented Dickey-Fuller (*ADF*) test and Kwiatkowski–Phillips–Schmidt–Shin (*KPSS*) test are conducted to examine and determine the stochastic signal of all-time series of dependent and independent variables.

Results and discussion

Data preprocessing

The first step in the data preprocessing is to normalise the time series of dependent and independent variables and to detect and treat the outliers as well (as mentioned in section 3.2). Figs. 2 and 3 highlight the differences between the raw data and normalised and cleaned data.

It should be noted that in the current study, the main emphasis will be oriented toward the stochastic component only (as previously mentioned in section 3.2). To develop a water demand model based on climatic factors, water consumption and climatic factors time series should first be decomposed utilising the pre-treatment signal approach. Fig. 4 shows the normalised and cleaned water time series coupled with the first four signals (trend, seasonal, stochastic, and noise). The stationarity of the stochastic signal for the all-time series is assessed and confirmed by applying *ADF* and *KPSS* tests.

Table 1 shows the difference in correlation coefficient between dependent and independent variables in raw and stochastic stages. It is obvious from this table that the values corresponding to climatic factors in stochastic are much higher than the counterpart values in the raw data such as the *R* between water consumption and precipitation increased from -0.535 to -0.931.

In the last section of data pre-processing, it is worth mentioning the necessity to determine the highly correlated predictors (climatic factors) and avoid multicollinearity at the same time. According to the Tolerance technique in section 3.2, the scenario of selecting the best model input is repeated several times to choose predictors with a Tolerance coefficient not less than 0.2. Accordingly, Table 2 reveals that three climatic factors include P, S_{rad}, and T_{dp} are determined to be the optimum scenario that has coefficients of more than 0.2 meaning that the violation of the multicollinearity assumption does not exist.

Model configuration

The systematic configuration of the ANN model instead of the trial-and-error technique is necessary to build an accurate water demand prediction model. Accordingly, five hybrid metaheuristic algorithms (MVO-ANN, SMA-ANN, BSA-ANN, CSA-ANN, and MPA-ANN) were used to locate the optimal hyperparameters (*Lr*, *N1*, and *N2*) of the ANN model. Five swarm sizes (10, 20, 30, 40, and 50) were attempted in this paper by combining different algorithms with ANN and each swarm for each algorithm was implemented five-time to get the optimal solution e.g., MPA-ANN algorithm in Fig. S4. After that, the optimal swarm for each algorithm was selected to compare it with other swarms for the same algorithm as depicted in Fig. S5. From the figure, one could see that the best swarms are 30 for CSA-ANN, 40 for MPA-ANN, and 50 for SMA-ANN, MVO-ANN, and BSA-ANN algorithms.

Among all the implemented five hybrid metaheuristic algorithms, it was noticed that MPA-ANN was superior to the other algorithms (Fig. 5). The MPA-ANN hybrid algorithm yields the least fitness function (*RMSE*) of 0.003993 after 42 iterations (lower iterations compared with the rest algorithms). As such, adopting MPA-ANN is feasible and warranted in the current study. So, the 40 swarms of the MPA-ANN algorithm presented *Lr*, *N1*, and *N2* values of 0.213, 7, and 1, respectively.

Evaluation of the model performance

After integrating the ANN approach by determining the optimum hyperparameters, the model runs several times to locate a better network (weights and biases) that can precisely forecast the monthly stochastic signal of water demand. Various kinds of statistical tests were applied to evaluate the capability of the ANN approach to generalise stochastic water demand data depending on climatic factors in the validation phase.

Five different statistical indicators were used to gauge the performance of the model as presented in Table 3. The *CE* and *NSE* assess the linear dependency between observed and predicted water demand, while *MAE*, *RMSE*, and *MBE* evaluate the non-linear dependency between observed and predicted water demand. According to the limitation in section 3.5, the ANN model offered good accuracy.

The estimated model was further validated to double-check the model power to accurately predict water consumption in the city of Baghdad. The target data of water consumption (in the x-axis) was plotted versus simulated data (in the y-axis), with a 95% confidence interval (*CI*)

(Fig. 6). It is noticeable that the target and simulated data reveal a high level of consistency with R=0.978, which supports the good accuracy of the prediction model based on the limitation in section 3.5.

According to the utilised statistical tests, the model demonstrated a good performance to forecast water consumption data in the validation stage.

Discussion

The selection of the stochastic component improved the correlation coefficients to climatic factors much higher than the counterpart values in the raw data. For example, the R between water consumption and precipitation increased from -0.535 to -0.931. Then, it was shown that the tolerance technique was very helpful in selecting the best model input among the total nine independent variables. Three climatic factors, namely P, S_{rad}, and T_{dp} are selected to be the optimum scenario with tolerance coefficients of more than 0.2 which means no multicollinearity exists.

When the five metaheuristic algorithms were combined to the ANN for obtaining the hyperparameters at various numbers of swarms are utilised, the optimum swarm size was different for each algorithm based on the RMSE value. The performance of the metaheuristic algorithms is then compared at these optimum swarm sizes as there was no direct guide for selecting a unique swarm size for all of them. Comparing the performance of the hybridised ANN, it was observed that the MPA-ANN algorithm provides the highest accuracy of prediction with the lowest RMSE value with relatively less iteration compared to other hybrid algorithms. Consequently, the ANN optimum hyperparameters values were determined. During the model validation process, it was shown that the model has a very good performance in forecasting future values of water consumption with a correlation coefficient value of *R* equals 0.978.

Wolpert and Macready (1997) mentioned that depending on the No Free Lunch (*NFL*) method, there is no specific theorem that can deliver the best solution compared with other theorems for all the optimisation issues. According to *NFL*, Faramarzi et al. (2020) develop the combined MPA theorem for guaranteeing the global solution, depending on several strategies and techniques during the optimisation. Different strategies of foraging have considerably inspired MPA in the biological interaction between the prey and predators. Consequently, the Brownian and *LF* distributions were designed not only to have a systematic explorer-exploiter tendency efficiently, but also to significantly enhance the capability of search in each implementation. These permitted the MPA algorithm to precisely locate the global optima of the optimisation issues considered in this research.

As a final note, since the size of the dataset used in this study can be considered relatively small, BO could have been used in conjunction with the MPA algorithm, aiming at increasing execution speed and accuracy. It is also worth noting that further methodological advances in the field of ANN may substantially increase model performance after a limited number of iterations (i.e. faster convergence time). Since the computation time was not a critical consideration in our study given that the measured data is obtained offline, we did not require to resource to the use of BO. The use of BO-based methods become more relevant when utilising online data as it involves a prolonged training time and becomes computationally expensive. The main objective of our study is to reduce the error between the measured data and the simulated one.

Conclusion

Precise water demand prediction has received significant attention from water companies in the last few decades due to water scarcity and the rapid growth of water consumption. A novel methodology was utilised in the present study to estimate the monthly stochastic municipal water demand based on some climatic factors by employing data over eleven years in Baghdad City. This is the first study that applies in Iraq, which is one of the hottest countries in the world. The methodology contains data preprocessing and five metaheuristic algorithms (MPA, SMA, CSA, BSA, and MVO) that are combined with an ANN model. Considering the outcomes, the data pre-processing was found to be a powerful technique that can be used to analyse and select the stochastic component of any time series by applying pre-treatment signal and to determine the best model input scenario by using tolerance. Accordingly, it provides a guide to choose suitable parameters that drive the water demand. The MPA was found to be a robust optimisation algorithm to select the best hyperparameters of the ANN approach. The developed methodology can accurately forecast the monthly stochastic signal of urban water demand based on various statistical tests. These findings are of considerable significance to water utilities to plan, review, and compare the availability of freshwater resources and increase water requests. Finally, it can be concluded that this methodology can be suggested to be applied to other cities in the surrounding countries with various scales.

Data Availability Statement

Some or all data, models, or code used during the study were provided by a third party. (List items used.) Direct request for these materials may be made to the provider as indicated in the Acknowledgments.

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Table 1. The correlation between dependent and independent factors in raw and stochastic stages.

Data	T_{max}	T_{min}	T_{mean}	P	$wind$	S_{rad}	T_{dp}	RH	S_p
Raw	0.558	0.585	0.571	-0.535	0.396	0.453	0.376	-0.541	-0.523
Stochastic	0.92	0.93	0.926	-0.931	0.835	0.728	0.794	-0.917	-0.869

Table 2. Collinearity statistics to the chosen predictors.

Predictors	Tolerance coefficient
P	0.35
S_{rad}	0.23
T_{dp}	0.33

Table 3. Statistical indicators of MPA-ANN model in the validation phase.

Data	MAE	$RMSE$	CE	NSE	MBE
Validation Stage	0.0057	0.0071	0.998	0.975	-0.0007

List of Figures

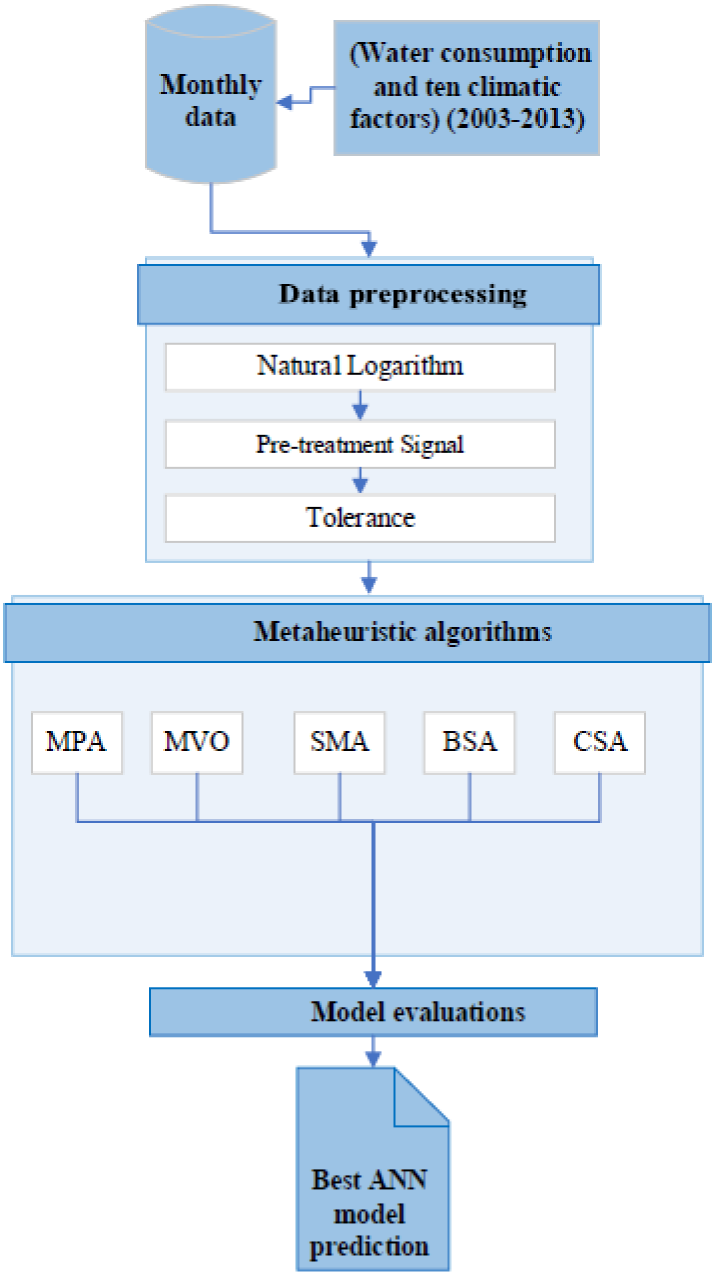

Fig. 1. Flowchart showing the steps required to forecast future municipal water demand.

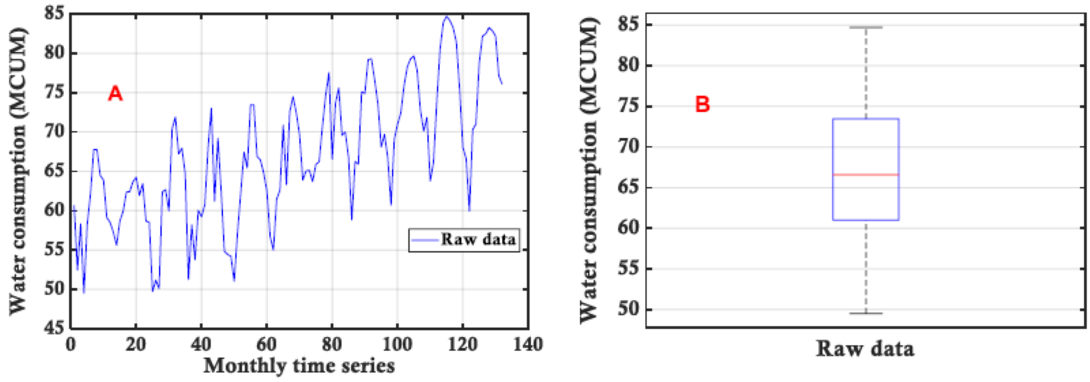

Fig. 2. A) Monthly raw time series, B) box-plot of urban water consumption for Baghdad City.

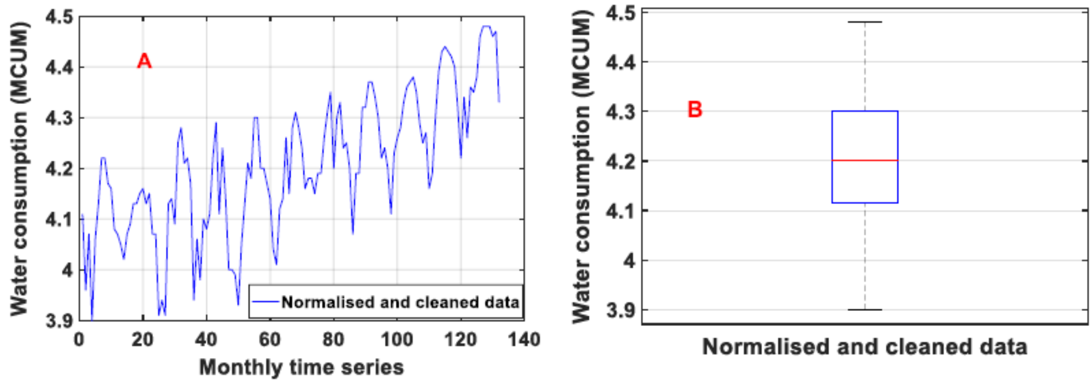

Fig.3. A) Monthly normalised and clean time series, B) box-plot of urban water consumption.

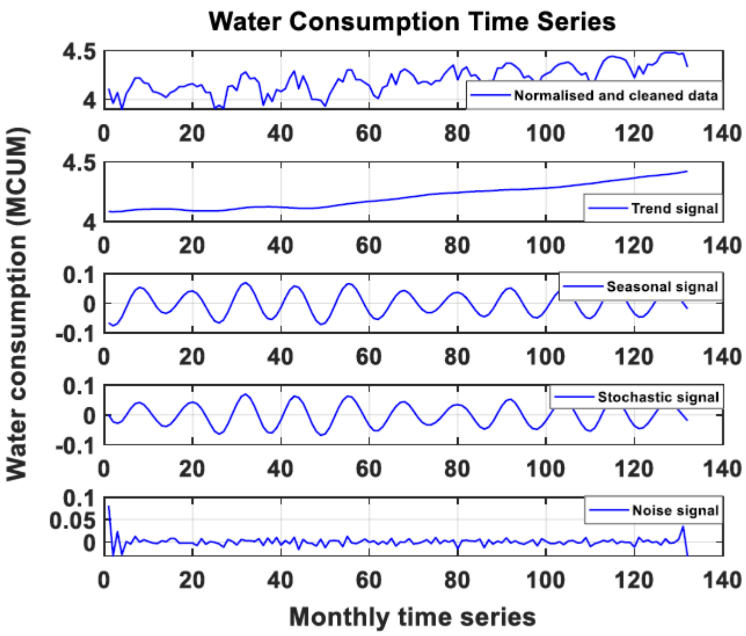

Fig. 4. Normalised and cleaned data and the first four signals obtained by pre-treatment signal.

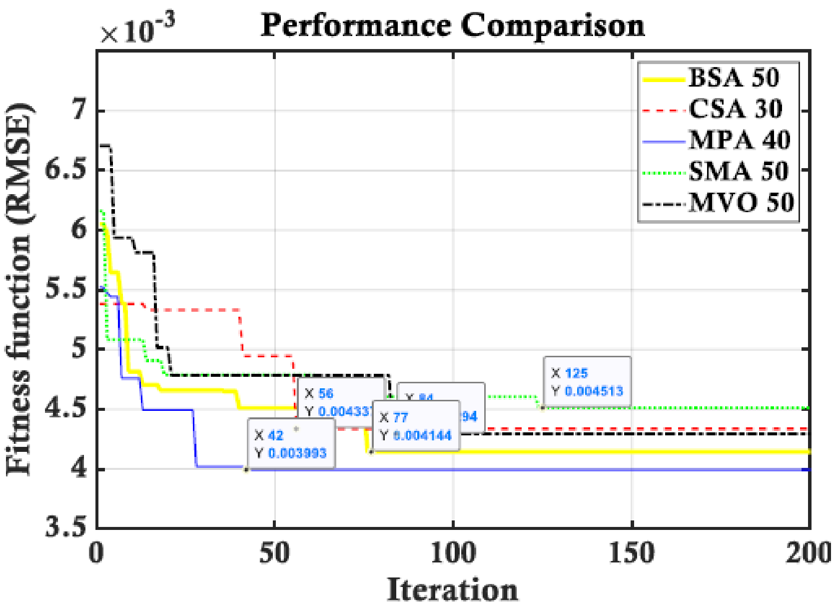

Fig. 5. Performance comparison among five hybrid algorithms.

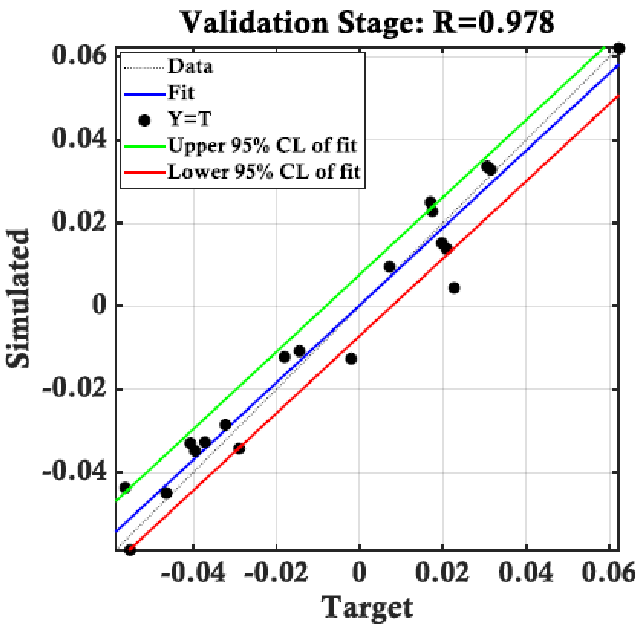

Fig. 6. Target water consumption data versus simulated in the validation stage.