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Modeling and Forecasting of Water Demand in the City of Istanbul Using Artificial Neural Networks Optimized with Rao Algorithms

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Abstract
In this study, a hybrid artificial neural network (ANN)-Rao series (Rao_1, Rao_2, and Rao_3) algorithm model was developed to analyze water consumption in Istanbul province, Turkey. A multiple linear regression (MLR) model was developed and an ANN was also trained with back-propagation (BP) artificial bee colony (ABC) algorithms for comparison. Gross domestic product and population data were treated as independent variables. To test the accuracy of the presently developed hybrid model, its outputs were compared with those of ANN-BP, ANN-ABC, and MLR models. Error values calculated for the test set indicated that the ANN-Rao_3 algorithm outperformed the MLR, ANN-BP, and ANN-ABC reference models as well as ANN-Rao_1 and ANN-Rao_2 algorithms. Therefore, using the ANN-Rao_3 model, water consumption forecasts for Istanbul province were generated out to 2035 for low-, expected-, and high-water demand conditions. The model-generated forecasts indicate that the water requirements of Istanbul in 2035 will be between 1182.95 and 1399.54 million m^3, with the upper-range estimates outpacing supplies. According to low and expected scenarios, there will be no problem in providing the water needs of Istanbul until 2035. However, according to high scenario, water needs of Istanbul will not be provided as of 2033.Therefore, water conservation policies should be enacted to ensure provision of the water needs of Istanbul province from 2033 onward.

Keywords Water demand forecasting · Rao algorithms · Neural networks · Istanbul

1 Introduction

Fresh water is a critical resource for all of humanity. Due to climate change-associated drought, fresh water resources are declining in many regions of the world, including in Turkey. According the United Nations World Water Council, the World Resources Institute, and the World Health Organization, water scarcity was uncommon in the 1950s, but 26 countries with a combined 300 million people were facing fresh water scarcity by the 1990s. These organizations are warning that by 2050 there may be severe water shortages in some 66 countries, which together are home to two-thirds of the world's human population [1]. Thus, the projected trend is pointing to a substantial risk of an impending global water crisis.

Currently, per capita human water consumption is around 800 m^3 per year, and approximately 1.4 billion people (20% of the world's population) do not have reliable access to sufficient drinking water of any quality, while even more people, some 2.3 billion, have insufficient access to clean potable water [1]. Although Turkey does exceed the threshold to be categorized as water-poor (< 1000 m^3/capita of water yearly), it experiences periods of water stress. Turkey is currently supplying approximately 1566 m^3/capita of water yearly to its residents and its net fresh water resource potential is 112 billion m^3. Turkey's population is expected to reach 100 million in 2030, at which time the amount of potable water per capita needed in Turkey is expected to be around 1120 m^3/year. Thus, it is imperative that Turkey develop plans that will enable it to use its water resources efficiently [1].

Approximately 20% of the drinking water consumed in Turkey is used in Istanbul province [2], which is the most populated province in Turkey with 15.8 million people in 2022 [3]. If necessary precautions are not taken, the increasing population of Istanbul will face water shortages. Thus, reliable water consumption forecasting models are needed

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to project future water demands and provide guidance for efficient water resource management, including planning for sustainable development projects that can ensure that future water demands will be met. Water consumption models with high predictive power can be employed to optimize efficiency by providing estimates of how much water should be allocated to which settlements as well as estimates of water demand across sectors defined by purpose.

Long-term water consumption projections (i.e., > 2 years) inform decisions regarding the construction of new water supply systems and the protection of water resources, and thus are important for ensuring water supply sustainability [4]. Long-term water consumption projections are particularly important for optimal management of water resources and reservoirs as well as for the design of hydraulic structures. Meanwhile, medium-term projections (3 months–2 years) are used to inform the expansion of existing water infrastructures, and short-term projections ($\leq$ 3 months) are necessary for ongoing optimization of the operations and maintenance of treatment-plant water wells and pumps in the water distribution network [4, 5]. Hence, all three temporal types of projections serve the provision of maintaining an adequate and continuous supply of clean water.

Currently, official water consumption projections in Turkey are created by employing the Turkish Bank of Provinces Method [6]. However, because this method does not account for the effects of changes in meteorological, technological, economic, and vitality conditions on water consumption, the water consumption estimates obtained using it cannot be considered sensitive. Given that policy makers need realistic water demand projections to ensure a sustainable water supply and the fact that water resource investment efficiency is closely related to accurate prediction of future water demand, the aim of this study was to develop a new robust and realistic water consumption forecasting model that employs a combination of ANN and Rao algorithms. The model was applied to Istanbul province, Turkey. Gross domestic product (GDP) and population data were inputted as independent variables and water consumption was the dependent variable produced. The annual water demand of Istanbul was thus estimated out to the year 2035.

2 Literature Review

Hybrid forecasting model methods can be created by combining techniques in a manner that eliminates the deficiencies of commonly used statistical or artificial intelligence methods. Recently, hybrid models consist of metaheuristic algorithms and ANNs have been growing in popularity. Uzlu et al. [7–10] used artificial bee colony (ABC), teaching–learning based optimization, Jaya and grey wolf optimizer algorithms, respectively, to develop ANN based hybrid methods. They used the population based metaheuristic algorithms instead of BP in the optimization of ANN weights to prevent memorization and stuck in local minima problems. In regression analysis, which is a statistical method, the coefficients of regression functions are determined using the least squares method. Since the least squares method is based on some precise mathematical expressions, it cannot fully reflect the relationship between independent and dependent variables. Therefore, hybrid methods have been developed using metaheuristic algorithms to optimize the coefficients of regression functions. Uzlu et al. [11] and Bayram et al. [12] used ABC and TLBO algorithms to optimize coefficients of regression functions.

The most commonly used statistical methods are time-series analytics, namely autoregressive integrated moving average (ARIMA) [13, 14] and regression analysis [4, 15, 16] methods. Among the artificial intelligence methods that have been used for water demand modeling, including ANNs, support vector machines [17, 18], and metaheuristic algorithms [19, 20], ANNs' high adaptability to nonlinear and complex situations makes them advantageous over other methods [14]. Water demand modeling studies using time series analysis methods constitute 30% of previous studies, while those employing ANN forecasting constitute 18.2% [21]. The ANN method is the second most preferred method in water demand modeling studies, followed by support vector machine and hybrid methods, which are the third and fourth most preferred methods, respectively [21]. Although hybrid methods generally give better results than singular methods, they have been under-utilized in water modeling studies [21] and their performance in water demand forecasting has not been investigated adequately. The present work addresses these deficiencies.

Both statistical and artificial intelligence methods have been used successfully in short-, medium- and long-term water consumption projections [22], though there have been far fewer long-term projections than short-term ones [21]. Detailed reviews of previous water demand forecasting studies have been published previously [21, 22]. In this section, an overview of the advantages and disadvantages of water demand modeling studies employing ANNs or hybrid methods is provided.

Many research groups have shown that ANNs can be highly effective for modeling water demands. For example, Adamowski [23] found that ANN modeling outperformed multiple linear regression and time-series analysis modeling for peak daily water demand. In a study comparing monthly water demand forecasting models in which socioeconomic and climatic factors were inputted as independent variables, Firat et al. [24] found that ANN models outperformed regression models. Ghiassi et al. [25] found that an ANN model performed better than an ARIMA model for forecasting urban water demand. Behboudian et al. [26]

showed that an ANN model yielded superior long-term urban water demand forecasting than a linear regression model. Employing temperature, relative humidity, wind direction, wind speed, and population data as independent variables, Vijai and Sivakumar [27] showed that their newly constructed ANN model for estimating water demand in the European Union outperformed regression models. Additionally, Tiwari et al. [28] showed that an ANN model simulated the daily urban water demands in Calgary, Canada accurately, Bennett et al. [29] introduced an ANN model for forecasting residential water end-use demand, and Koo et al. [30] used a radial basis function-ANN model, as well as ARIMA and quantitative multi-model predictor plus models, to develop longer short-term memory techniques for modeling water demand.

On the other hand, Herrera et al. [31] described a support vector regression model based on hourly water demand data that outperformed ANN, projection pursuit regression, multivariate adaptive regression splines, and random forest models in the modeling of the water demands of a city in southeastern Spain. Additionally, in Rezaali et al.'s [32] comparative study, a random-forest method provided more accurate and reliable water demand forecasts than ANN, least squares support vector machine, or regularized extreme learning machine models.

Several groups have combined modeling strategies. Notably, Li et al. [33] developed a method for modeling urban annual water demand that combines regression and ANN techniques and uses population, GDP, annual average temperature, and greenery coverage data used as input values. Their results have shown that the model is reliable and feasible. Adamowski et al. [34] developed a hybrid wavelet transform-ANN model based on daily total precipitation and daily maximum temperature data that they went on to show was more robust than comparator regression and ARIMA models. Kofinas et al. [35] proposed a hybrid ARIMA-ANN model to forecast water demand on the island of Skiathos in Greece, and Altunkaynak and Nigussie [5] used an ANN with a multiplicative season algorithm to model monthly water consumption in Istanbul, Turkey based on 23 years of historical monthly water consumption data (January 1992–December 2014). They tested their model relative to empirical data but did not make any forward predictions. Shirkoohi et al. [36] developed a genetic algorithm-optimized ANN for water demand prediction that outperformed ARIMA and pattern-based models. Hu et al. [37] developed a hybrid model based on isolation forest and adaptive signal decomposition techniques for forecasting water demand that produced more accurate results than support vector regression and ANN techniques. Azadeh et al. [38] showed that a hybrid approach consisting of an ANN, fuzzy linear regression, and analysis of variance yielded superior water consumption forecasting relative to several other models.

Recently, effective ANN models have developed with metaheuristic algorithms for use in many fields, including energy [9], coastal engineering [39], and hydrology [40]. Hence, it is of great interest to explore how the incorporation of newly developed algorithms, including the Rao algorithm series, may improve ANN performance. The Rao algorithm series, developed in 2020 [41], has already been used successfully in civil engineering [42], mechanical engineering [43], and optics [44] applications. Notably, Rao algorithms have been shown to enhance ANN training outcomes more effectively than other metaheuristic algorithms [45, 46].

Given the promisingly robust outcomes obtained with Rao algorithms thus far, the aim of this study was to develop and test a new and innovative ANN-Rao method of water demand projection. To the best of this paper's authors' knowledge, an ANN-Rao method has not yet been used in the field of water consumption/demand modeling. Because the Rao algorithm series does not require any specific control parameters, it is highly amenable to ANN model creation.

The presently introduced ANN-Rao method was tested by modeling water demand in Istanbul province, the province with the largest economy and population in Turkey. Long-term water consumption projection for Istanbul is lacking in the literature. Here, consumption projections were produced out to 2035, extending beyond previously reported shorter-term estimates. Moreover, the presently developed projection is more reliable than prior projections owing to its low error values and being based on more recent data. The population and economy of Istanbul are increasing, elevating the consequences of having water resource management and planning based on realistic projections for the region. Moreover, projecting water consumption in Istanbul is of national importance for Turkey.

3 Methodology

Water demand forecasting ANN and (MLR) multiple linear regression models were developed. The quantity of layers of the network architecture, type of transfer functions employed, and quantity of hidden-layer neurons were determined by trial and error informed by previous experiences [9, 10]. A three-layer network architecture was selected (Fig. 1). Hidden mid-layers with 5, 10, 15, and 20 neurons were considered, always with a 2-neuron input layer (one for each independent variable: GDP and population). For each algorithm, the number of neurons in the hidden mid-layer was tested as 5, 10, 15 and 20, and the neuron numbers that gave the best results were taken into account. A single neuron constituted the output layer, which yielded the dependent variable of water consumption. A hyperbolic tangent sigmoid and a linear function were used as the activation function

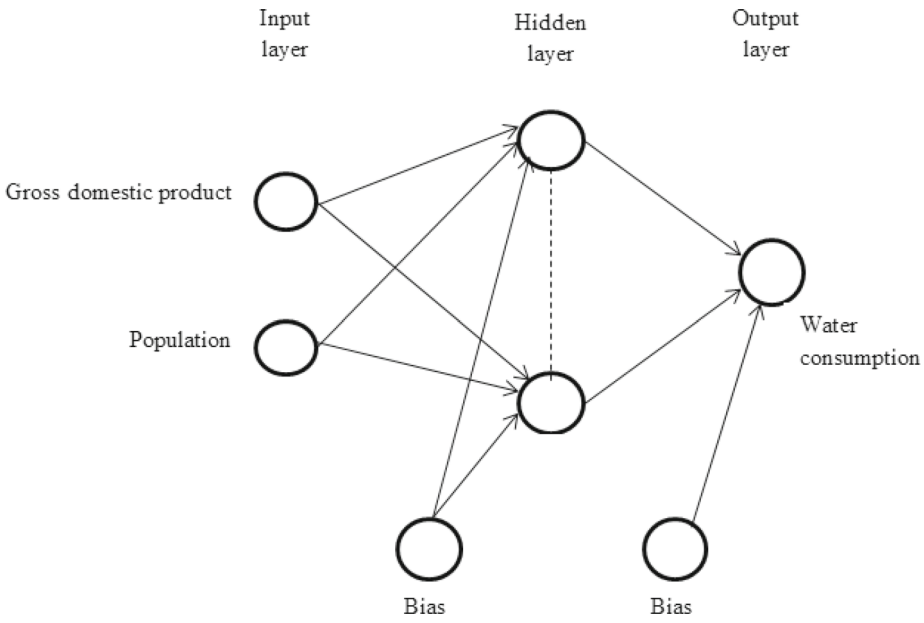


Fig. 1 Proposed ANN model for water demand prediction

between the input and middle layer and as the transfer function between the intermediate layer and the output layer, respectively.

ANN-retained information was represented in the weights of inter-neuron connections. BP, ABC and Rao series algorithms (Rao-1, Rao-2, and Rao-3) were used to determine optimum weights. In order evaluate the adequacy of the proposed model, MLR analysis was made. The SPSS 17 statistical software was used for the analysis. In MLR analysis, the coefficients of the linear function are determined based on the least squares method. Regression analysis, which is a statistical method frequently used in the forecasting of water consumption, was used as the classical method. In order to investigate the accuracy of the derived MLR model, R^2 and adjusted R^2 values as well as p values showing the significance of the model were examined. The BP algorithm is well known and explained in detail elsewhere [7, 47]. Similarly, the ABC algorithm is widely used population-based meta-heuristic approach that was developed by Karaboga [7]. Since the ABC algorithm is an old, robust and frequently used algorithm, detailed information about the ABC algorithm has been previously presented by many researchers in the literature [7, 11]. To avoid repetition, detailed information about the ABC algorithm is not given here. Detailed information about the Rao series of algorithms is presented in the next section.

3.1 RAO Algorithm Series

The Rao-1, -2, and -3 algorithms are population-based algorithms that perform optimization by considering the best, worst, and possible solutions [41], as depicted in the Rao algorithm flowchart in Fig. 2. During optimization, candidate solutions are developed and compared, with the value of an objective function serving as a criterion. The optimization process continues until better values for the objective function are found. In the Rao algorithm series, new solutions are developed using Eqs. (1), (2), and (3):

$$\text{Rao - 1} \ : \ X_{\text{new},\,i} = X_i + r * (X_{\text{best}} - X_{\text{worst}}) \tag{1}$$

$$\text{Rao - 2: } X_{\text{new},\,i} = X_i + r_1 * (X_{\text{best}} - X_{\text{worst}}) + r_2 * \left(\left|X_i \text{ or } X_j\right| - \left|X_j \text{ or } X_i\right|\right) \tag{2}$$

$$\text{Rao - 3: } X_{\text{new},\,i} = X_i + r_1 * (X_{\text{best}} - |X_{\text{worst}}|) + r_2 * \left(\left|X_i \text{ or } X_j\right| - (X_j \text{ or } X_i)\right) \tag{3}$$

In the above equations, i represents the number of the candidate solution and the variables r, r_1, and r_2 are numbers that can take random values between 0 and 1. X_{best}, X_{worst}, and $X_{\text{new},i}$ represent the best, worst, and current candidate solutions in the population at the tth iteration. The size of the population is equal to the number of candidate solutions. X_j is the randomly selected candidate solution from the current population and must be differ from X_i.

As can be seen from Eq. (1), only the best and worst solutions are taken into account to develop a new candidate solution in the Rao-1 algorithm. In this way, new candidate solutions move away from the worst solution and converge to the best solution. In Rao-2 and Rao-3 algorithms, in addition to the best and worst solution, X_j is considered in order to develop a new solution. The objective function values of X_i and X_j are compared such that their difference must be positive. That is, "$\left(|X_i| - \left|X_j\right|\right)$" is used if X_i is a better solution

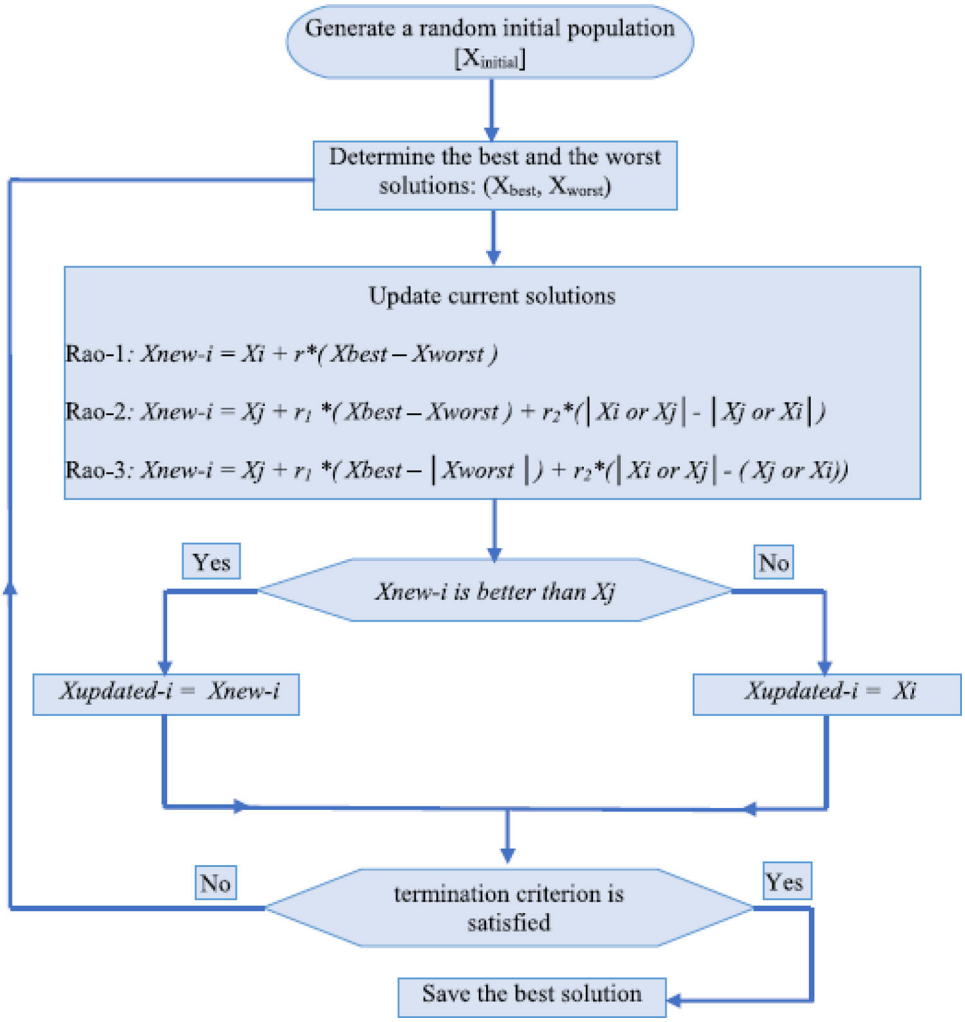


Fig. 2 Flow chart of the Rao algorithms [48]

than X_j, whereas "$(|X_j| - |X_i|)$" is used if Xj is the better solution.

The Rao algorithm optimization process consists of the following seven steps: (1) set population size and maximum iteration number; (2) initialize population randomly and calculate objective function (fitness) values; (3) determine the best (X_{best}) and worst (X_{worst}) solutions based on the objective function's values; (4) update solutions using Eqs. (1), (2), and (3); (5) calculate the objective function value of new solution obtained in step 4; (6) if the new solution is better, it replaces the old one, otherwise the old solution is kept; (7) iteration number is incremented by one. If the maximum number of cycles is reached, the program stops and the best solution is reported; if not, the cycle starts again from step 3.

4 Study Area

Istanbul province is located on the western edge of Turkey in the Marmara Region, straddling both sides of the Strait of Istanbul (Bosphorus), which is the waterway that connects the Black Sea and the Sea of Marmara, and that separates Asia and Europe (Fig. 3) [49]. It is the most populous province in Turkey, with over 98% of the provincial population residing within the eponymous city of Istanbul. For simplicity, in this paper, the term Istanbul refers to the study area of Istanbul province, which includes the eponymous city of Istanbul and its surrounding metropolis. Istanbul, inclusive of the city of Istanbul and the surrounding towns in the province, represents one of the largest metropolitan areas in both the OECD and the world [49].

Istanbul is an immigration epicenter within Turkey owing to its high economic activity and its well-developed education, health, and industrial sectors, which provide ample job opportunities and good-quality living conditions. Istanbul's population increased by 33% between 2004 and 2021 [3]. In 2021, Istanbul accounted for 18.7% of Turkey's total population and 13.9% of the total number of immigrants in Turkey [3], while Istanbul's GDP accounted for 30.4% of Turkey's national GDP [50].

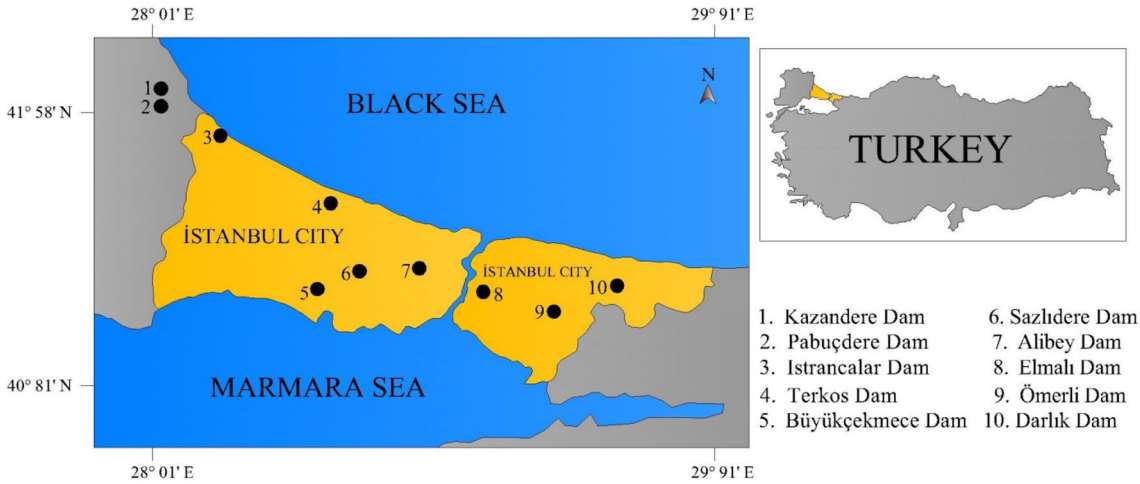


Fig. 3 Location of the city of Istanbul and her water resources

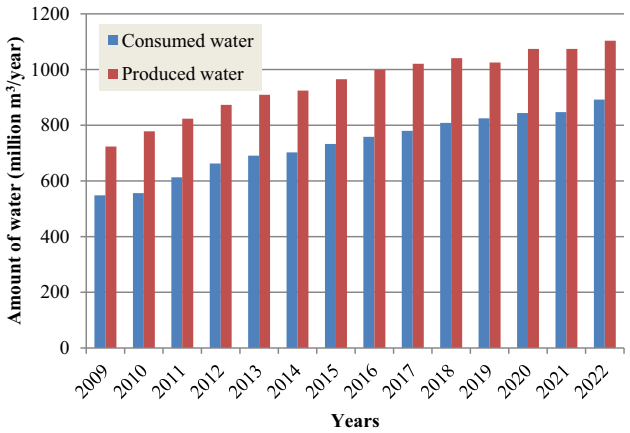


Fig. 4 Produced and consumed water in Istanbul province [2]

As a burgeoning population center, Istanbul's water demands are on the rise. The amount of water consumed in Istanbul constitutes approximately 20% of the total water volume consumed in Turkey [2]. The amounts of fresh water consumed and delivered annually in Istanbul are presented in Fig. 4. Note that the data show a continuous increase in water production and consumption. The seepage loss ratio decreased from 24.2% in 2009 to 19.16% in 2022 [2]. Almost all of the water consumed in Istanbul is obtained from surface water sources maintained by rain. In times of drought, water collected by dams is used to maintain water distribution to the city of Istanbul (Fig. 3). The total capacity of all dams supplying water to the city is only 80% of the city's annual water needs [2]. Hence, a rainless year would result in completely empty dams. Fortunately, there are no expectations of extended rainlessness in Istanbul. Water is also supplied to the city from regulators installed in the water basins of Melen Stream, Yeşilçay, and Istrancalar, though such water requires purification processes. In 2021 and 2022, the Melen and Yeşilçay regulators provided approximately 60% of Istanbul's water needs [2]. Drought affecting the natural water basins where these regulators are located represents a serious potential threat to Istanbul's water supply. According to the Turkish State Meteorological Service, between October and December 2022, standardized precipitation index of the Marmara Region was calculated as − 1.64 [51]. Therefore, there was a nationwide drought, with "extraordinary" or "very severe" drought areas in the Marmara region [51]. Although Turkey is expected to face substantially drier and hotter conditions in the future, given the ongoing long-term decreasing trend in precipitation in the country, there is not yet a systemic water supply projection study planned for Istanbul. Given the water consumption projections that have been made for Turkey, it is necessary that Turkey plan for future drought mitigation.

5 Applying BP, ABC, and Rao Algorithms to ANNs

Before starting the ANN weighting optimization process, a solution range for the weights was determined. In the first iteration, the weights are selected randomly by the algorithm so that they remain within solution range. An estimated network value is calculated for the selected weight values. The error value is calculated by comparing the predicted value with the observed value. The root mean square error (RMSE) objective function was used as the error function in this study. In subsequent iterations, the algorithm attempts to reduce the error value by choosing new values close to the initial weight values. The optimization process terminates when the objective function's value falls below the acceptable error value or the maximum number of iterations has been reached. RMSE

is calculated using the following formula.

$$\mathrm{RMSE} = \left[\frac{1}{n}\sum_{k=1}^{n}(y_k - o_k)^2\right]^{1/2} \tag{4}$$

where o_k, y_k, and n are the predicted value, observed value, and data quantity, respectively. Only the training set of data is used during ANN weighting optimization.

ANN performance was assessed by measuring learning ability according to minimal error values calculated for the test set based on RMSE, average relative error (RE), and mean absolute error (MAE). Average RE, coefficient of determination (R^2), and MAE are calculated using Eqs. 5, 6, and 7, respectively. The optimized model with the smallest error value for the test set was selected as the best model in terms of predictive power. In addition, the best model results were evaluated in terms of correlation coefficients (R values) and Nash–Sutcliffe efficiency (NSE) value. R and NSE values were calculated as in Eqs. (8–9).

$$\text{average RE} = \frac{\sum_{k=1}^{n}\left(\frac{y_k - o_k}{y_k}\right)}{n} \times 100 \tag{5}$$

$$R^2 = \left(\frac{\sum_{k=1}^{n}(y_k - \overline{y})^2 - \sum_{k=1}^{n} y_k - o_k)^2}{\sum_{k=1}^{n}(y_k - \overline{y})^2}\right) \tag{6}$$

$$\mathrm{MAE} = \frac{1}{n}\sum\nolimits_{k=1}^{n}|(y_k - o_k)| \tag{7}$$

$$R = \frac{\left(\sum_{k=1}^{n}(o_k - \overline{o})\left(y_k - \overline{y}\right)\right)}{\sqrt{\sum_{k=1}^{n}(o_k - \overline{o})^2 \sum_{i=}^{n}\left(y_k - \overline{y}\right)^2}}, \tag{8}$$

$$\mathrm{NSE} = 1 - \frac{\sum_{k=1}^{n}(y_k - o_k)^2}{\sum_{k=1}^{n}\left(y_k - \overline{y}_k\right)^2}. \tag{9}$$

The most important feature that distinguishes Rao algorithms from other population-based algorithms is its low number of control parameters: only population size and maximum number of cycles. The control parameter values were set based on values that gave good results previously [10, 42, 43]. For the development of the ANN models, the population size was set to 50 and the maximum number of cycles was set to 1000 (for BP, ABC, and RAO algorithms). The run number was 10 for the BP, ABC, and RAO algorithms. Weights were optimized within the range of [− 1, 1]. For the BP algorithm, the learning and momentum coefficients were within the range of [0.1, 1] and the first-iteration weight values were randomly determined within the range of [− 0.01, 0.01] [10]. For the ABC algorithm, limit value was set as 100. The minimum value to be reached by the objective function was 8×10^{-8} for all algorithms.

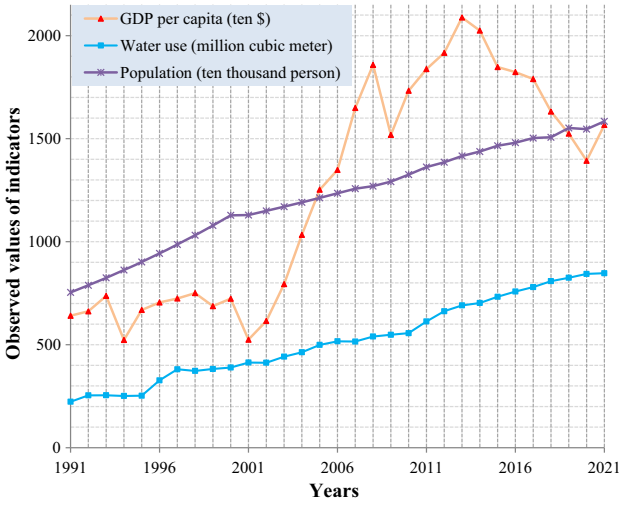


Fig. 5 Variations in dependent and independent variables [3, 50, 53]

The running times of the proposed methods are as follows. While the analysis is carried out in a very short time in the MLR method, it takes a very long time in the ANN method depending on the run number, number of iterations, and number of neuron in the hidden layer. In this study, MLR analysis was carried out within one minute. In the ANN method, 1000 iterations were performed 40 times for each algorithm. To perform 1000 iterations, the ABC algorithm ran for about an hour, the Rao algorithms ran for about 40 min, and the BP algorithm ran for about 10 min. Working times may increase or decrease slightly depend on the number of neurons in the hidden layer. Since the BP algorithm has a simple structure, analysis time is short. In the ABC algorithm, analysis takes a long time due to the large number of operations performed and the complex structure of the algorithm.

6 Data Used in the Study

Water consumption is affected by many factors, including economic factors (GDP, employment rate, per capita income), demographic structure (population distribution by age and gender), weather conditions (maximum and minimum temperature, precipitation), water resource availability, user prices for water, and loss/leakage rates in water distribution systems. Generally, socio-economic factors are used to forecast long-term water demand, while factors related to weather and water price are used for short- and medium-term water consumption projections [52]. Population-related parameters are used in all water consumption projections.

Because increases in industry, agriculture, and service production levels produce increases in GDP, GDP is considered to be a primary economic indicator [9].Considering the historical data in Fig. 5, it is seen that GDP changes

in direct proportion to water consumption. As the GDP increases, the amount of water used in agriculture, industry, and service sectors increase. GDP is closely related to water consumption. Meanwhile, population growth is a main factor underlying increased water use. Therefore, GDP and population data were utilized as input data to forecast Istanbul's water demand. Data from the time period of 1991–2015 were used for model development and data from the period of 2016–2021 were used to test model output accuracy. Water consumption data were obtained from the Istanbul Metropolitan Municipality [53]. GDP and population data were obtained from the Turkish Statistical Institute (TURKSTAT) [3, 50]. Summaries of the obtained data are presented in Fig. 5.

The data were subjected to standard normalization before being entered into the model. Because the activation functions selected for the ANN in this study generally produce values between [0, 1], the data range was reduced to [0.1, 0.9] thereby shortening the optimization process and increasing the model's predictive power. The equation used for normalization is presented below.

$$\text{Normalized value} = \left[\frac{\text{Raw value} - \text{Minimum value}}{\text{Maximum value} - \text{Minimum value}}\right] \times (0.9 - 0.1) + 0.1 \tag{10}$$

7 Performance Evaluation of the Forecasting Model

Three-layer perceptron-type ANNs consisting of an input layer, hidden layer, and output layer were used, as shown in Fig. 1. GDP and population values were used in the input layer and forecasted water consumption value constituted the model output. BP, ABC, and Rao algorithms were utilized for ANN weight optimization. A MLR model was developed to compare the proposed model with traditional methods. The developed regression model is presented by Eq. 11. In Eq. 11, unit of water consumption, GDP, and population is million cubic meter, ten $, and ten thousand persons, respectively. p value of population and GDP are 2.38×10^{-14} and 2.4×10^{-3}. Because the p-values of the independent variables is smaller than 0.001, the GDP and the population data are significant predictors for water demand modeling. In addition, p value of MLR model was obtained as $1.72 * 10^{-20}$. Therefore, it can be concluded that MLR model are significant at the 95% confidence level. Model performance was inferred from error values calculated for the training-set and test-set data (Table 1). In the MLR model, the R^2 and the adjusted R^2 values for the training set were calculated as 0.741 and 0.736, respectively. Both R^2 and p values show that the accuracy of the model is at an acceptable level. The contribution rates for the independent variables in the MLR model were calculated as 75.64% for the population and 24.36% for the GDP. Therefore the population was statistically determined as the most significant independent variable for water demand.

$$\text{water consumption} = -485.776 + 0.035 * (\text{GDP}) + 0.765 * (\text{population}) \tag{11}$$

According to the training-set error values (Table 1), Rao algorithms performed better than BP and ABC in ANN training. In ANN models trained with the BP and ABC algorithm, the smallest error values were obtained from the model with 5 neurons in the hidden layer [ANN-BP (2–5–1) and ANN-ABC (2–5–1)]. In the ANN models optimized with Rao algorithms, the smallest error values were obtained from the model (2–10–1) with 10 neurons in the hidden layer for the Rao_1 algorithm, and from the models (2–15–1) with 15 neurons in the hidden layer for the Rao_2 and Rao_3 algorithms. Typically, increasing the number of neurons in the middle layer boosts ANN performance. The RMSE values calculated using training-set data for the regression model, ANN-BP (2–5–1), ANN-ABC (2–5–1), ANN-Rao_1 (2–10–1), ANN-Rao_2 (2–15–1), and ANN-Rao_3 (2–15–1) models are 47.090 m^3, 36.335 m^3, 33.196 m^3, 24.211 m^3, 17.618 m^3, and 17.989 m^3, respectively. The smallest RMSE value for the training set was obtained from the ANN-Rao_2 (2–15–1) model. The smallest average RE and MAE values for the training set data were also obtained from the ANN-Rao_2 (2–15–1) model (Table 1). Based on RMSE values, the Rao_1, Rao_2, and Rao_3 algorithms increased ANN training performance by 33.37%, 51.51%, and 50.49%, respectively, compared to BP. Similarly, considering the RMSE values the Rao_1, Rao_2, and Rao_3 algorithms perform better than ABC for ANN training, respectively, by 27.07%, 46.93%, and 45.81%. The largest error values for the training set were obtained from regression analysis. According to MAE values calculated for the training set, ANN-BP (2–5–1), ANN-ABC (2–5–1), ANN-Rao_1 (2–10–1) ANN-Rao_2 (2–15–1), and ANN-Rao_3 (2–15–1) models outperformed the MLR model respectively, by 8.87%, 27.95%, 42.87%, 62.40%, and 59.28%. The largest R^2 value for the training set was found for ANN-Rao_2 (2–15–1) which has the smallest error values.

Model-predicted values are compared to real data in Fig. 6; although it is difficult to distinguish visually which model converges more to the real data in the graph, the error values (Table 1) indicate unambiguously that the ANN-Rao_2 (2–15–1) model converges most closely to the real data. Due to the potential for a memorization artefact, test-set error values were considered when determining each model's predictive power.

Table 1 The model results for the training and test set data

Method	RMSE (m^3)		MAE (m^3)		Average RE (%)		R^2		Maximum RE (%)		NSE	
	Training set	Test set	Training set	Test set	Training set	Test set	Training set	Test set	Training set	Test set	Training set	Test set
MLR	47.090	72.565	33.719	70.516	10.50	8.562	0.741	0.510	10.081	11.647	0.892	0.578
ANN-BP (2–5–1)	36.335	45.366	30.725	42.945	8.249	5.259	0.861	0.542	9.082	7.139	0.911	0.621
ANN-ABC (2–5–1)	33.196	35.937	24.296	32.815	7.246	4.024	0.865	0.554	9.078	6.580	0.916	0.654
ANN-Rao-1 (2–10–1)	24.211	21.073	19.265	16.994	5.277	2.088	0.875	0.678	7.540	4.454	0.951	0.784
ANN-Rao-2 (2–15–1)	17.618	19.973	12.677	16.398	3.354	1.989	0.895	0.721	7.633	3.735	0.972	0.850
ANN-Rao-3 (2–15–1)	**17.989**	**17.649**	**13.729**	**14.197**	**3.551**	**1.715**	**0.891**	**0.804**	**6.452**	**3.121**	**0.971**	**0.908**

The bold value is the error value for the proposed model

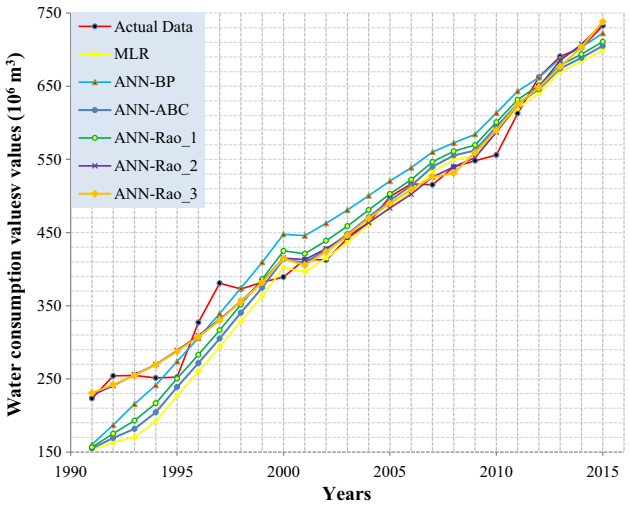


Fig. 6 Performances of the MLR, ANN-BP (2–5–1), ANN-ABC (2–5–1) ANN-Rao_1 (2–10–1), ANN-Rao_2 (2–15–1), and ANN-Rao_3 (2–15–1) for the training set

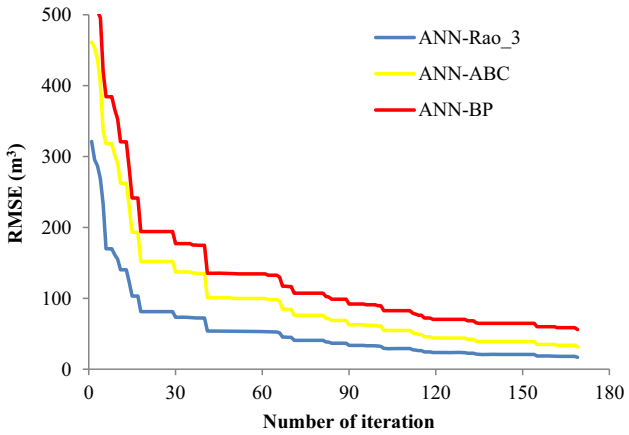


Fig. 7 The convergence history of the ABC, Rao_1, Rao_2, and Rao_3 algorithms for ANN training

Whereas the Rao_3 algorithm found the optimal weights for the ANN in the 168th iteration, the ABC and BP algorithms found these weights in the 326th and 714th iteration, respectively. The convergence history of the Rao_3, ABC and BP algorithms for the ANN are given in Fig. 7. In the 168th iteration, the convergence values of the Rao_3, BP and ABC algorithms were 17.989, 33.733, and 58.653, respectively. Therefore, the Rao_3 algorithm performed better than the ABC and BP algorithms in terms of the convergence velocity.

The smallest error values and the largest R^2 values for the test set were obtained from the ANN-Rao_3 (2–15–1) model (Table 1). The R^2, RMSE, MAE, and average RE values calculated for the ANN-Rao_3 (2–15–1) model are 0.804, 17,649 m^3, 14,197 m^3, and 1.715%, respectively. Although the smallest error values for the training set are obtained from the ANN-Rao_2 (2–15–1) algorithm, the best model is the ANN-Rao_3 (2–15–1) model, which has smaller error values for the test set. Considering the RMSE values calculated for the test set, ANN-Rao_3 (2–15–1) performs 75.68%, 61.09%, 50.89%, 16.24%, and 11.64% better than the MLR model, ANN-BP (2–5–1), ANN-ABC (2–5–1), ANN-Rao_1 (2–10–1), and ANN-Rao_2 (2–15–1) models, respectively (see Fig. 8 for graphical comparison of test

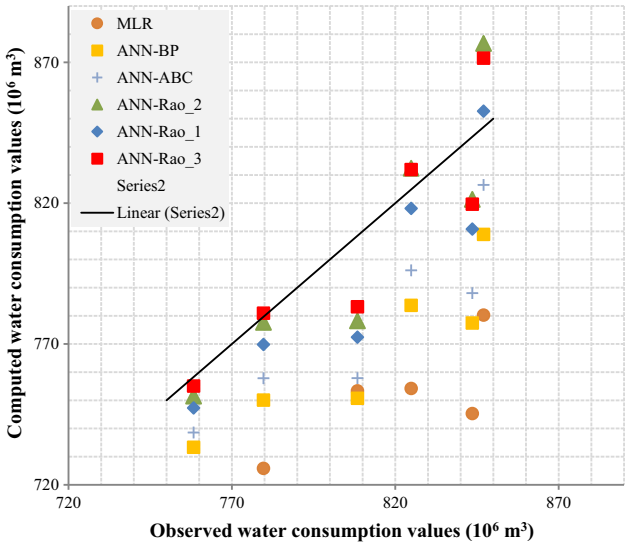


Fig. 8 Performances of the MLR model, ANN-BP (2–5–1), ANN-ABC (2–5–1), ANN-Rao_1 (2–10–1), ANN-Rao_2 (2–15–1), and ANN-Rao_3 (2–15–1) for the test data

set data). The maximum RE values for the test set are 11.647%, 7.139%, 6.580%, 4.454%, 3.735%, and 3.121% for the MLR model, ANN-BP (2–5–1), ANN-ABC (2–5–1), ANN-Rao_1 (2–10–1), ANN-Rao_2 (2–15–1), and ANN-Rao_3 (2–15–1), respectively. The ANN-Rao_3 (2–15–1) model estimations are the closest to the real values (Fig. 8).

The *R* and NSE values calculated for the ANN-Rao_3 (2–15–1) model using training-set (0.964 and 0.971, respectively) and test-set (0.894 and 0.908, respectively) data affirm that the predictive power of the proposed model is acceptable. Indeed, Rao algorithms increased ANN performance accuracy (see data in Tables 1 and 2). Rao_3 algorithm performs better than Rao_1 and Rao_2 algorithms owing to its greater number of interacting parameters.

8 Future Predictions of Water Demand

Using the proposed model, water consumption values were estimated for Istanbul out to the year 2035 under three scenarios. In scenario 1 (low-demand), scenario 2 (expected-demand), and scenario 3 (high-demand), socio-economic development and population growth are assumed to remain below average, to match TURKSTAT expectations [54], and to outpace expectations, respectively. The assumed GDP growth rates for scenarios 1, 2, and 3 are 2.50%, 4.11%, and 7.0%, respectively. The data used in the scenarios are presented in Tables 2 and 3.

Water consumption estimates for Istanbul produced with the ANN-Rao_3 model for the low-, expected-, and high-demand scenarios are reported in Table 4. Istanbul's water needs in 2035 in these scenarios are projected to be 1182.95, 1281.47, and 1399.54 million m^3, respectively. Full use of Istanbul's water resources would amount to an annual water production of 1620 million m^3 before accounting for leakage from distribution systems and water tanks. Adopting Istanbul's seepage loss ratio from 2022, which was 19.16%, the maximum amount of water that would be expected to actually reach consumers in Istanbul is 1293.44 million m^3/year. In scenarios 1 and 2, the water needs of Istanbul can be met until 2035. However, in scenario 3, the water supply to Istanbul would fail to meet the population's needs by 2033. Moreover, in scenarios 1 and 2, supplies in 2035 would be approaching maximum water availability, which is an indicator of near-future water supply insufficiency.

As can be seen in Fig. 9, the water consumption values obtained from this study are smaller than those estimated previously by Ertem and Doğan [55]. According to Ertem and Doğan [55], Istanbul's water consumption values in 2025, 2030, and 2035 will be 1266.13, 1409.05, and 1533.46 million m^3, respectively. The present modeling data suggest that the water needs of Istanbul in 2025, 2030, and 2035 will be in the ranges of 956.79–1021.86, 1073.14–1204.22, and 1182.95–1399.54 million m^3, respectively. To obtain their estimates, Ertem and Doğan [55] used the Turkish Bank of Provinces Method, which is based solely on statistical formulas and does not account for socio-economic effects and thus tends to produce overestimates of water consumption. Although reliance on this method helps to ensure that water demand is not underestimated, it can have a negative impact of the efficiency of water resource management and lead to suboptimal investment decisions regarding water distribution systems and water structures.

9 Conclusions

Forecasting water consumption in Istanbul is extremely important for enabling water management infrastructure investments to be made in an efficient and sustainable way in Turkey. Water consumption in Istanbul was projected under three scenarios with ANN-Rao algorithm hybrid models. Average RE, RMSE, and MAE values calculated for training and test sets indicated that the ANN-Rao_3 model produced more accurate projections, relative to real-world data, than MLR model, ANN-BP, ANN-ABC, ANN-Rao-1, and ANN-Rao_2 models. These data suggest that Rao_3 use should be preferred over BP and ABC use in ANN modeling of water use. In addition, the proposed method performed better than classical regression analysis. The ANN-Rao_3 algorithm predicted future water consumption with acceptable accuracy, affirming the suitability of Rao algorithm use in the field of water demand modeling.

Table 2 The GDP and population data used in scenarios

Year	GDP ($) per capita			Population (10^6)		
	Low growth rate 2.5%	Average growth rate 4.11%	High growth rate 7.0%	TURKSTAT [51]		
				Low scenario	Expected scenario	High scenario
2022	16,057.650	16,309.873	16,762.620	16.022	16.139	15.906
2023	16,459.091	16,980.208	17,936.003	16.208	16.349	16.068
2024	16.870.569	17,678.095	19,191.524	16.391	16.556	16.226
2025	17,292.333	18,404.665	20,534.930	16.570	16.759	16.381
2026	17,724.641	19,161.096	21,972.375	16.745	16.959	16.531
2027	18,167.757	19,948.617	23,510.442	16.916	17.155	16.678
2028	18,621.951	20,768.506	25,156.173	17.084	17.348	16.821
2029	19,087.500	21,622.091	26,917.105	17.247	17.536	16.959
2030	19,564.687	22,510.759	28,801.302	17.406	17.720	17.093
2031	20,053.804	23,435.951	30,817.393	17.560	17.900	17.222
2032	20,555.150	24,399.169	32,974.611	17.708	18.075	17.344
2033	21,069.028	25,401.975	35.282.833	17.852	18.246	17.461
2034	21,595.754	26,445.996	37.752.632	17.990	18.412	17.572
2035	22,135.648	27,532.926	40.395.316	18.123	18.573	17.677

Table 3 Scenarios for Istanbul's water demand

Scenarios	GDP	Population
Scenario 1	The low growth rate (about 2.50%)	The population data obtained from TURKSTAT low scenario [51]
Scenario 2	The average growth rate (about 4.11%)	The population data obtained from TURKSTAT expected scenario [51]
Scenario 3	The high growth rate (about 7.0%)	The population data obtained from TURKSTAT high scenario [51]

Table 4 Future projections of water demand in million cubic meter according to scenarios and Ertem and Doğan [55]

Year	Scenario 1	Scenario 2	Scenario 3	Ertem and Doğan [55]
2022	885.605	903.237	920.718	–
2023	909.369	931.201	953.669	–
2024	933.108	959.545	987.388	–
2025	956.792	988.234	1021.855	1266.135
2026	980.386	1017.223	1057.041	–
2027	1003.854	1046.461	1092.909	–
2028	1027.159	1075.897	1129.423	–
2029	1050.266	1105.476	1166.539	–
2030	1073.141	1135.145	1204.220	1409.051
2031	1095.747	1164.731	1242.411	–
2032	1118.053	1194.173	1281.072	–
2033	1140.035	1223.410	1320.165	–
2034	1161.673	1252.384	1359.660	–
2035	1182.954	1281.047	1399.537	1533.458

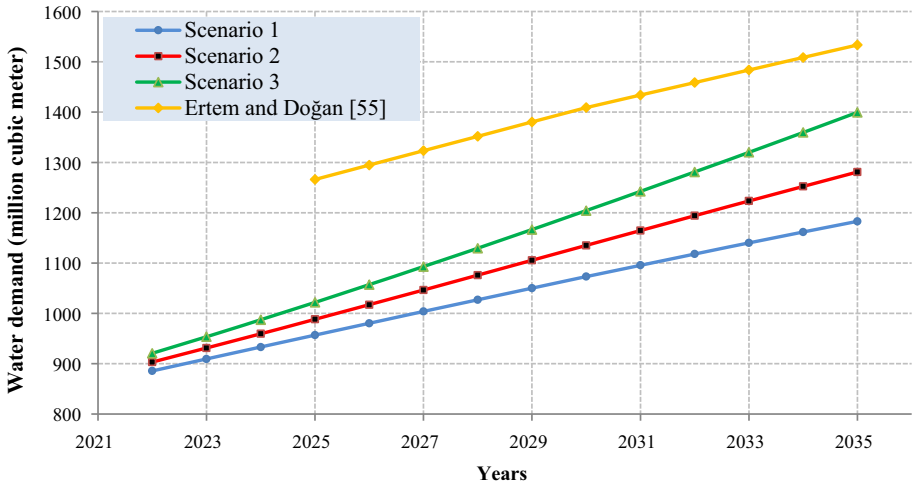


Fig. 9 Comparison of the three scenarios, and Ertem and Doğan [55] for Istanbul's water demand

The water needs of Istanbul in 2035 were projected herein to be somewhere between 1182.95 and 1399.54 million m^3, with low- and expected-demand scenarios being meetable, albeit with small margins, in 2035. In the high-demand scenario, water supply strain would become a problem by 2033. Thus, to avoid water supply problems, it is essential that Turkey develop additional water resources and make plans that will enable it to use its existing water resources more efficiently. It is hoped that the results of this study will help policy makers make well-informed decisions related to urban planning and water resource management.

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Data Availability Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Conflict of interest The author has no relevant financial or non-financial interests to disclose.

Ethics Approval There are no relevant waivers or approvals.

Consent to Participate Not applicable (there is only one Author).

Consent for Publication The author allows publication if the research is accepted.

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