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WATER RESOURCES MANAGEMENT USING ANFIS, ANN AND MULTIPLE LINEAR REGRESSION

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Abstract
Water resources management helps with decision-making so that regional water demand is distributed effectively, preventing waste and shortages. This study's goal is to assess the water resources in the Democratic Republic of the Congo's Kinshasa location. Thus, the explanatory variables and factors pertaining to the community, water consumption, economy, and resource availability were determined. Three statistical and artificial intelligence based models were developed (ANN, ANFIS, and MLR) covering the dataset from the years 1961–2021. To identify the most effective predictive model, research and analysis were conducted. The outcomes demonstrate that artificial neural networks provide the greatest prediction performance across the three scenarios for the models developed. The results show how well the explanatory elements that were discussed might forecast water demand. To estimate water demand and ensure the sustainable use of water resources, machine learning models were implemented using an ensemble of single predictor models. It is possible to apply the best forecasting model elsewhere.

Introduction
Although it is indisputable that air and water are essential for human living, a sizable portion of the global population lacks access to a sufficient water supply system. These days, it is understood that water use and consumption are physiological, social, economic, political, and cultural issues. (Ashok K. Sharma and Prabhata K. Swamee, 2008).
Water is used by all living things, including plants, animals, and humans. Earth would not support life if the latter did not exist. Water is a necessity for all life. A framework known as water resource management allows us to ensure that an industrial or residential region has access to clean drinking water. Water resource management encompasses various aspects, such as health, economic, architectural, and other relating to water quality and delivery. Limiting water waste and poor management, which can lead to resource and financial waste as well as the potential for the spread of some water-borne illnesses, is another concern. The Democratic Republic of Congo has abundant resources, primarily in freshwater, yet the water sector remains a significant concern for the nation. The DRC's drinking water supply is currently experiencing a severe crisis. Actually, just 26% of people have access to potable water. UNEP (2011). Apart from the intricate

socioeconomic and rural circumstances within the nation, the water sector has experienced excellent growth due to political determination and foreign assistance.

Acknowledging the nation's struggles with water scarcity and management, improved methods for forecasting and allocating the nation's resources must be sought after. The squandering of water resources can lead to tensions and cultural, social, and political crises in many countries, particularly in semi-arid and desert regions. The nation's socioeconomic progress and development are greatly influenced by the management of water resources. Numerous investigations have demonstrated that various models, particularly machine learning models, can be used to manage water resources (Janusz A. Starzyk, 2015).

Regretfully, classic linear models based on imprecise estimation, assumptions, and linear approximation are still in use in the Democratic Republic of the Congo. Over the course of the last 20 years, a variety of models covering the prediction of water demand and water management employing artificial neural networks (ANNs), multi-linear regression (MLR), and support vector machine (SVM) have been developed. (Msiza I. S., et al., 2008). Therefore, it is imperative and required to bring up the subject of machine learning techniques in the context of Democratic Republic of the Congo's water resource management.

In order to predict water resource management for Lubumbashi City while taking into account various combinations of input parameters, the study aims to develop the potential of machine learning based models, specifically Artificial Neural Networks (ANNs), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), and Conventional Multi-Linear Regression Models (MLR). Using the input data from the individual models, set up, develop, and implement three strategies to increase the prediction performance's efficiency. The performances of the several models were compared in order to select the best model. Through the provision of information on the water demand situation in the Lubumbashi region to water supply departments and decision makers, the study's findings will contribute to the development of effective strategies for managing water resources and the long-term stability of the water supply.

The format of the paper is as follows: In brief, pertinent studies are reviewed in Section 2. The processes are explained in Section 3. Section 4 reports the results of the model test, and Section 5 wraps up.

1. Literature Review

In order to mimic the rainfall-runoff mechanism, Nourani et al. (2011) carried out research using two hybrid artificial intelligence systems. The hybrid model that was created by combining ANN, SARIMAX, and ANFIS was able to capture the seasonal and nonlinear aspects of the runoff time series data. The rainfall-runoff modeling was much enhanced by those hybrid multi-variable models. To simulate the nonlinear behavior of the events, a nonlinear kernel structure was constructed utilizing the hybrid model. The time series' autoregressive pattern was the only thing that the ANN and ANFIS models could keep an eye on.

A study on a moving window model for short-term water demand forecasting utilizing previously collected data was published by Elana Pacchin et al (2017). For short-term demands in a water distribution system, a novel model was put forth. Using a pair of coefficients, the model makes predictions for the next twenty-four hours based on demand data that are updated at each stage of the process. The suggested model has a good predictive ability, as demonstrated by its application to real-world situations and by comparison with the results of another short-term prediction model based on the same data.

In Bentolhoda Asl-Rousta et al.'s (2018) study, twelve SWAT models of the Sirwan River Basin in Iran were employed and compared collectively to examine various hydrological models. The twelve models differed in terms of calibration models, number of gauged stations, number of parameters, and calibration procedures. AICc, CAIC, AICu, AIC, SIC, HIC, SICc, and HICc were the eight MSC that were utilized for the validation and calibration of the outperforming midel. The ranking results and the two scenarios under investigation were found to be significantly related.

Jiping et al. (2019) developed a trend-following model to extract prospective hydrological information from time-series meteorological data. Their study established a model structure by analyzing time-series models, rules, trends, and confidence and support trends to address data paucity issues while capturing information and building models. The aim is to rectify the shortfall in efficient data capture, hidden model and law discovery within time series data in traditional time series research. The results showed a pattern of short-term evaporation and precipitation trends, constantly increasing or decreasing, and often remaining consistent within the study area.

In Tazania's Wamu Ruvu Basin, Mngereza Miraji et al. (2019) studied the effects of water demand and how it might affect surface water resource management in the future. The household and agricultural sectors were the main focus of the overall estimate of the anticipated increase in water use. The water demand was assessed and the implications of several aspects, including population increase and economic development, were assessed by the authors using an arithmetic and mathematical model. Tanzania's current trend (CT) in conjunction with demand side management (DSM) and economic growth (EG) scenarios were considered in the research.

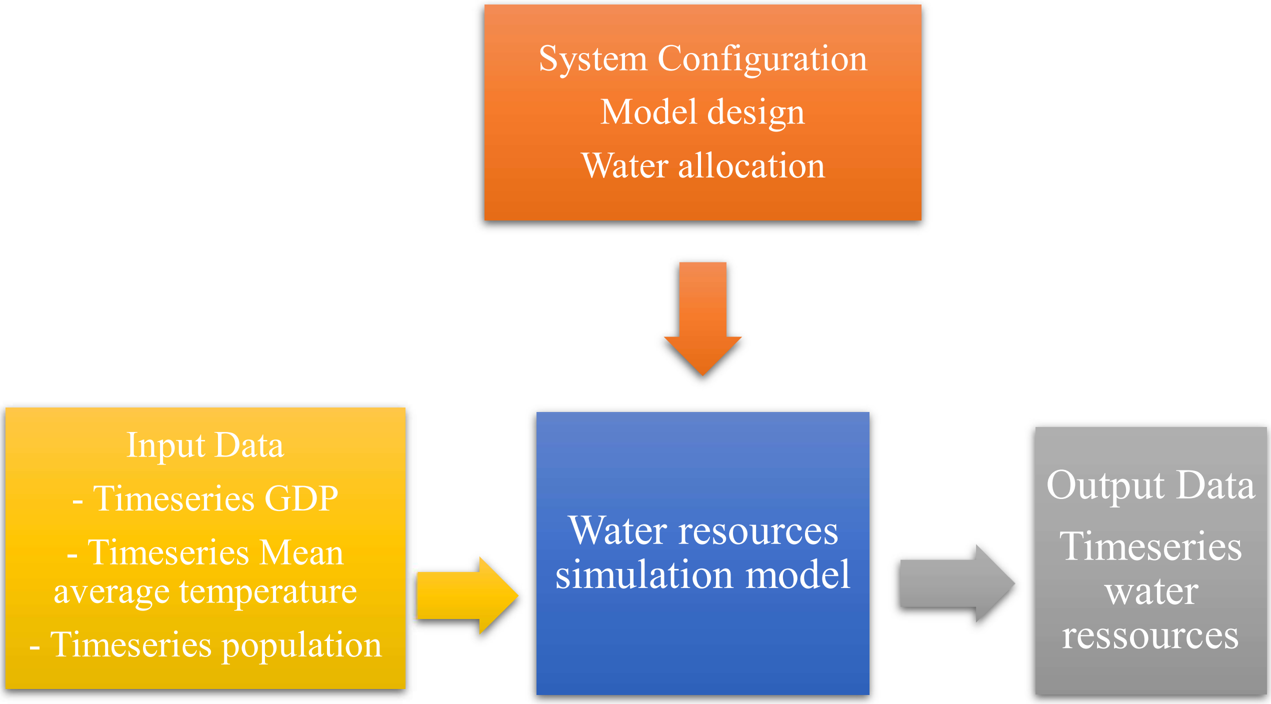
In 2020, Romain Kasongo and colleagues designed and sized a water supply network system for JOLI SITE. The initial step in the process was building a database using the study's cartographic data. Second, the water delivery system's performance was assessed and its flaws were found using EPANET software. The research produced an efficient on-demand power system that satisfies perimeter water needs while ensuring effective water distribution management. The network's simulation results under actual operating conditions were determined to be good. It displays technology that satisfies the criteria set in this field in addition to being tailored to the needs of operation and maintenance.

Elahe Kalashak (2021) studied how machine learning can be used to estimate water use. He forecasted the hourly water use in a sustainable smart city using machine learning techniques. To carry out the research, seven models were created, and the best outcome was determined by comparing them.

2. Materials and methods

In order to manage water resources and do machine learning modeling, this study employed ANN, ANFIS, and MLR. The steps in the suggested methodology are as follows:

3.1. Model Configuration



3.2. Data Preprocessing

In AI-based research, data normalization is commonly employed to guarantee that all variables are treated equally and that their dimensions are eliminated. The main benefits of data normalization are as follows: (1) The disadvantage of larger numeric ranges masking the smaller ones is removed by data normalization. Data normalization lessens the difficulties associated with computing (Abdullahi and Elkiran, 2017). As a result, the data were changed as follows:

$$x_i' = \frac{x_i - \min(x)}{\max(x) - \min(x)} \qquad \text{(I)}$$

Where, the normalized value, the observed value, the maximum value, and the minimum value are represented by X'_i, X_i, X_{min}, and X_{max}.

3.3. Modelling

3.3.1. Artificial Neural Networks (ANN)

As a forecasting tool, ANN is frequently used in hydrology and water resource research. Engineers often use feed forward back-propagation (BP) network models for artificial neural networks (ANNs). It has been demonstrated that every engineering problem may be forecasted and simulated using the three-layer BP network model (Nourani et al., 2011).

Of all the AI techniques, ANN is a compelling method that can deal with noisy, nonlinearity, and dynamic data, especially when the underlying physical relationships are not well understood. In AI-based research, it is most common for all variables to have equal consideration and for their d According to Nourani et al. (2020), this emphasizes the value of the ANN as a powerful tool in data-driven field for continues time process implementation.

The following figure presents the architecture of ANN model:

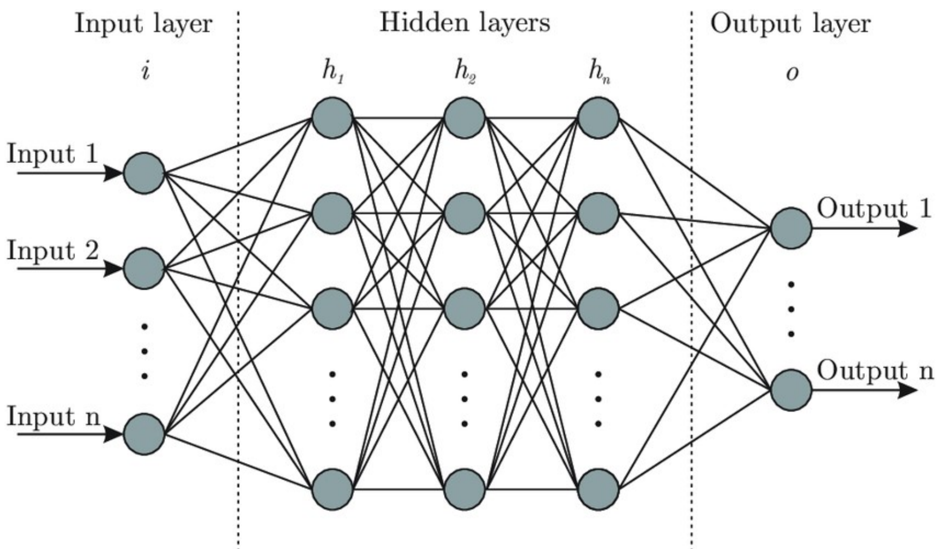


Figure 1. Architecture of an ANNs model (Facundo Bre et al, 2018)

3.3.2. Adaptive Neuro Fuzzy Inference Systems

The majority of AI-based studies demand that each variable be given the same level of consideration. In the research on neural networks, the term "neurofuzzy" describes fuzzy logic modeling methods that use special learning algorithms to the fuzzy inference system (FIS). Jang (1993) originally presented ANFIS, a unique technique, in the construction of the Neural Fuzzy System. It employs the training strategy of the neural network.

A fuzzy Sugeno model called the ANFIS is incorporated into the adaptive systems framework to aid with learning and adaptability. With the help of this framework, ANFIS modeling becomes less dependent on expert knowledge and more methodical.

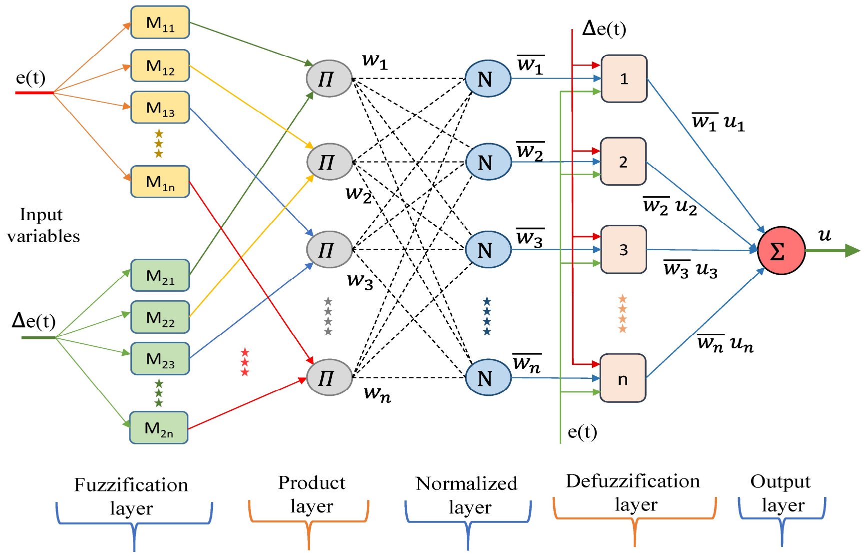


Figure 2. ANFIS model architecture (Ahmed F. Bendary et al, 2021)

The Fuzzy if-then rules are formulated by the equation (II) and (III) where the number of rules is indicated by n. Take note that the fuzzy membership functions are represented by: M_{1i} and M_{2i}. The linear components of the corresponding n_{th} rule are represented by Pn, Qn, and Rn.

$$R_n = if\ M_{1i}(e)\ and\ M_{2i}(\Delta e)\ \text{ then,} \qquad \text{(II)}$$

$$f = p_n e(t) + q_n \Delta e(t) + r_n \qquad \text{(III)}$$

Each node in the layer typically represents an adaptive function created by

$$M_{1i} = \frac{1}{1 + [\frac{x - c_i}{a_i}]^{b_i}} \qquad \text{(IV)}$$

Where the parameter set is represented by (a_i, b_i, c_i). Keep in mind that layer 2 represents the product inference layer, where a certain fuzzy rule determines how strongly each node called with P.

$$w_i = M_{1i}(e) * M_{2i}(\Delta e) \qquad \text{(V)}$$

The computed firing strength from the previous layer is normalized, and this is reflected in the third layer, which is a normalization one:

$$\overline{Wi} = \frac{w_i}{\sum_i w_i} \qquad \text{(VI)}$$

The normalized results from the third layer are received by layer 4. Observe that each node in this matching layer, which has a node function described as, indicates an adaptive mode (defuzzification).

$$\overline{W\iota}U = \overline{W\iota}(\, p_i e + \, q_i \Delta e + \, r_i) \qquad \text{(VII)}$$

Where u denotes the chosen control signal and (p, q, r) is the consequence parameter set. Keep in mind that in order to gather the output resulting piece of rules at the last layer, the summation of all inward signals must be computed.

$$\sum_i \overline{w\iota}U = \frac{\sum_i w_i U}{\sum_i w_i} \qquad \text{(VIII)}$$

3.3.3. Multi Linear Regression (MLR)

A tried-and-true method that dates back to Pearson's use in 1908, multiple regression is used to forecast the variance in an interval dependency based on linear combinations of independent variables that can be either dummy, interval, or dichotomous. Finding out more about the link between a number of independent or predictive factors and a dependent or criteria variable is the main goal of multiple regression analysis.

Historically, the MLR technique was used to quantitatively characterize the linear connection of two or more parameters (independent predictor variables) and a predictand (dependent variable). Typically, (Nourani et al. 2019) represents the link between the n and y representing the predictors and dependent variables.

The MLR equation takes the following form:

$$y = \, b_1 \, x_1 + \, b_2 \, x_2 + \cdots + \, b_n \, x_n + c \qquad \text{(IX)}$$

Regression coefficients b_1, b_2..., b_n show how much the dependent variable y changes in response to a unit change in the corresponding independent variables. When all the independent variables are zero, the regression line intercepts the y-axis at a constant value, c, which represents the amount of the dependent variable y.

3.4. Model Training

Seventy percent of the total dataset was made up of random samples from 1961 to 2021, which made up the training data.

3.5. Model Testing

When evaluating statistical performance, two different standard statistical kinds were taken into consideration. The root mean square error (RMSE), and correlation coefficients (R) were applied. The test data model is made up of the remaining random samples, which make up 30% of the overall dataset for the years 1961 to 2021. These measures were taken into account because they were frequently used in studies on predicting water consumption. For each sample, the following methods of measuring the gap between actual and expected values were used:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=0}^{n-1}(y_i - \hat{y}_i)^2} \quad (X)$$

Where n, $\hat{y}_i$, y_i, mean the observed values, and anticipated values are. The root mean square error (RMSE), which is derived by squaring the errors, is used to quantify the accuracy of the projected values.

R^2 is a fit quality metric. It evaluates the proportion of variance that a model's explanatory components can account for:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (XI)$$

3.6. Case of Study: Kinshasa City

3.6.1. Study Region

It is without doubt that Kinshasa is not only the largest metropolis in central Africa but also the capital of the Democratic Republic of Congo. Cultural but also colonial value, Kinshasa contains several treasures throughout its extent. landmark of fishing and maritime trade at one time. Today Kinshasa is considered one of the fastest expanding and growing megacities. With a population of more than 16 million inhabitants, it is not only the most populated megacity of Africa but also of the DRC. It is the main economic, political and cultural center of the Democratic Republic of Congo and the third largest city in Africa. Covering some 9,965 square kilometers, Kinshasa encloses a vast, mostly low-lying crescent shape along the southern shores of the Malebo Basin, having an average altitude of around 300 meters. Kinshasa borders the provinces of Mai-Ndombe, Kwilu and Kwango to the east; the Congo River constitutes its western and northern borders, establishing a natural border with the Republic of Congo; to the south is the Kongo Central province. Kinshasa lies between latitudes 4° and 5° and longitudes 15° and 16°32' to the east.

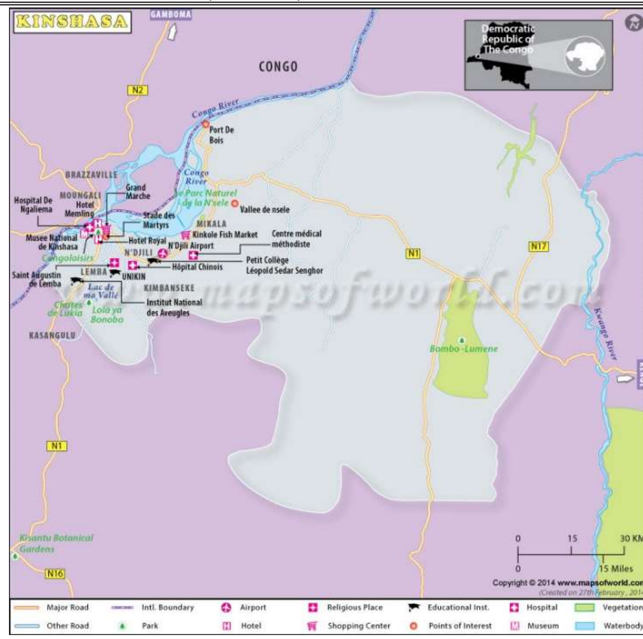


Figure 3. Map of the study area (Map of the World, 2023)

3.6.2. Dataset

In order to simulate water resources management, the following explanatory elements were selected based on the literature study, research plan, and several studies conducted over the years by various researchers:

- Water use: distribution of water among various sectors (residential, non-residential, municipal, etc.) and irrigated areas;
- Population growth in the community: annual figures;
- Availability of resources: average temperature and precipitation;
- Economy: GDP per capita

The World Bank Group provided the data for the other variables (mean temperature and mean precipitation) for the same time period. The Water Resources Society Reports and the International Organization (FAO) provided information on water use and irrigated area.

The table below included the basic variables and data.

Table 1. Data description for predictants

	Agricultural Land	*Population*	*GDP*	*Mean Average Temperature*	*Precipitation*
Min	*250500*	*1481820*	*1250.9804*	*23.68*	*1414.1*
Max	*337300*	*26681825*	*2882.8982*	*24.74*	*1528.74*
Average	*267697.8689*	*9726192.5*	*2001.3737*	*24.1952459*	*1485.607705*
Std	*25855.8664*	*7198193.8*	*447.77451*	*0.260292186*	*33.57150952*

In order to identify the optimal design and amplified models to prevent linearity and relationships between the input parameter values, a normalization and correlation coefficient calculation were performed. We have seen that irrigated land and precipitation had a high degree of correlation with different values for the five inputs; therefore, in order to get the optimum simulation, we have to discard them for the process's next phase.

Table 2. Correlation Coefficient of the parameters

	Agricultural land Thousand Hectare	*Year-end Population*	*Gross Domestic product*	*Mean Average Temperature*	*Yearly Mean Precipitation*
Agricultural land Thousand Hectare	*1*				
Year-end Population	*0.85134295*	*1*			
Gross Domestic product	*0.14032181*	*0.34142591*	*1*		
Mean Average Temperature	*0.36133989*	*0.67100445*	*0.45041202*	*1*	
Yearly Mean Precipitation	*0.80145877*	*0.99112845*	*0.42548774*	*0.71815664*	*1*

Nevertheless, using differents element as the predictand, Table 2 indicates that precipitation, and agricultural land are the best, and most sensitive predictors, respectively. This indicates that the precipitation and agricultural land variable have a higher linear association.

3. Results and discussion

There were two steps included in this investigation. To improve water resource modeling, the most suitable predictors were identified in the initial step by applying the approaches CC. Nonlinear models were developed to implement water resources management using AI-based models ANN and ANFIS, and they were related to linear MLR models.

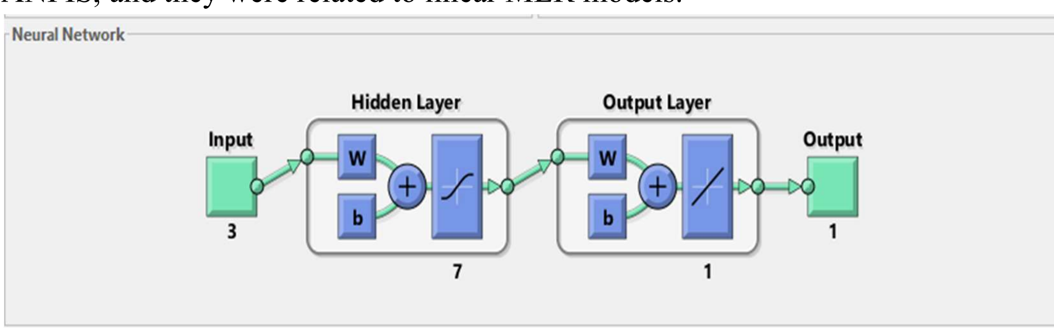


Figure 4. Optimal Neural Network Trained

A number of modeling techniques were taken into consideration for ANN in order to determine the most dependable and efficient performance. A trial-and-error method was used to choose the buried neuron numbers—which are crucial for AI-based modeling. The network parameters, such as the training function, transfer function type, learning algorithm, etc., were used to create the ANN model.

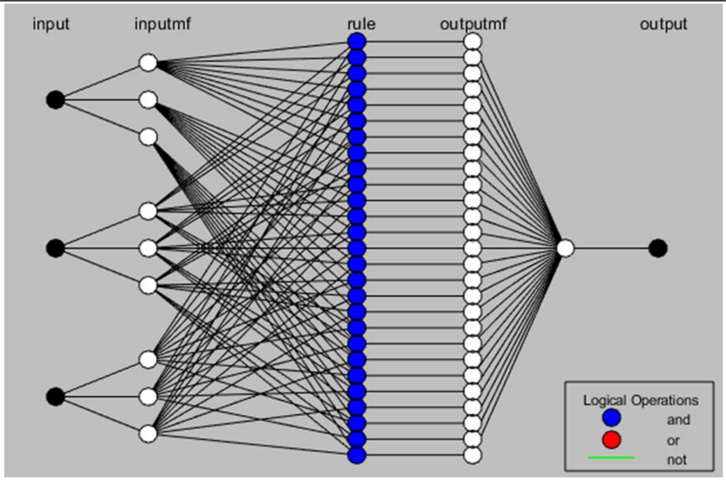


Figure 5. ANFIS Structure Trained

A hybrid optimization approach was utilized to calibrate the Sugeno type fuzzy inference system for ANFIS modeling. A variety of membership functions, such as Gaussian, Triangular, and Trapezoidal, were employed. The network selection process was done through trial and error in order to arrive at the ideal ANFIS construction.

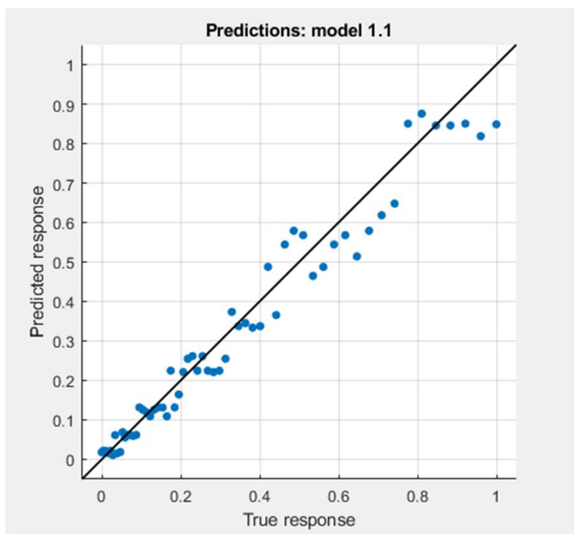


Figure 7. MLR Predicted plot

Table 3. Metrics Results

Metrics	ANN	ANFIS	MLR
R^2 (%)	99.99	96	96
RMSE*	0.000000047	0.000024	0.055856

RMSE is unitless because the data are normalized

The models are assessed using the R_2 and RMSE performance metrics, as shown in Table 3. It is evident from looking at the research case that the AI model ANN performs better than ANFIS and MLR respectively.

It is important to note that the FFNN model's construction requires careful consideration of the number of hidden neurons, training epoch number, and transfer functions. Because of its quick learning curve and excellent performance accuracy, Lavenberg Marquardt was selected as the BP training method for this study. Using various input combinations, four distinct FFNNs were trained for each output, and trial-and-error testing was used to identify the optimal design.

As indicated in Table 3, FFNN (3-1) with three inputs and one output neuron was determined to be the best for all three simulated variables. It is evident that the FFNN results generated are adequate for performance prediction, as evidenced by the R^2 and RMSE values shown in Table 3.

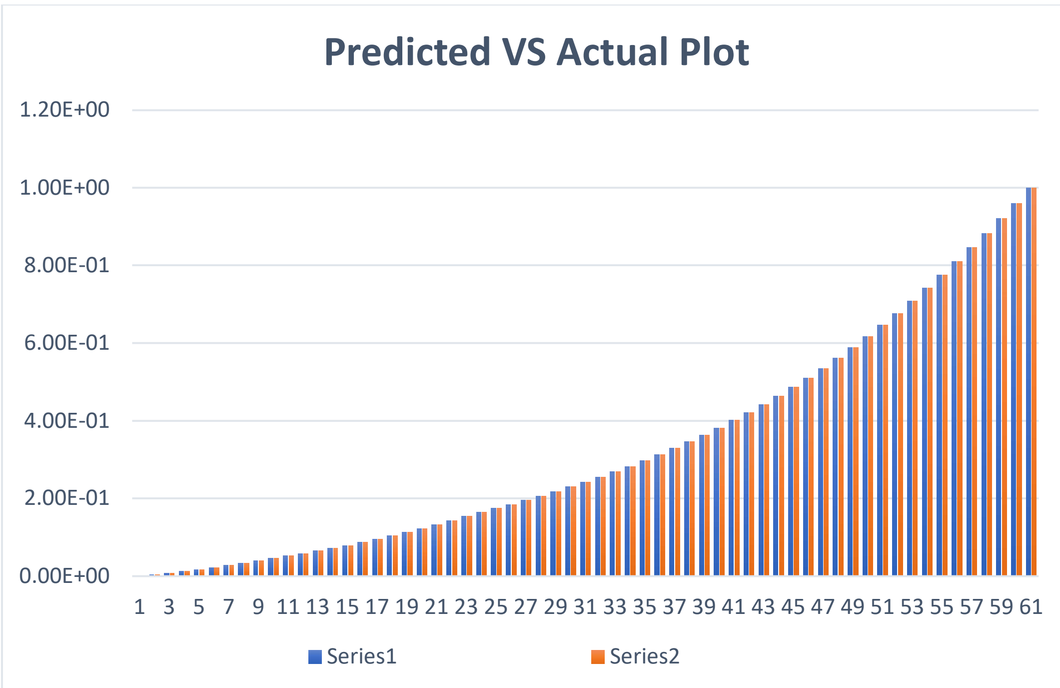


Figure 8. Predicted ANN vs Actual Plot

The water allocation that is expected and the water allocation that is available are shown by the blue and orange histograms, respectively. These ratings are kept track of for sixty years. The annual population growth for our case study, one of the explanatory variables included in the computations, explains why the demand for water grows at a consistent rate every year. On the other hand, the estimated water demand value demonstrates a variation in quantity over time, which is explained by the intricacy of the models employed and the way the model combines multiple elements to get the best outcomes.

4. Conclusion

Like in Kinshasa, many cities throughout the world are now facing severe water shortages. Estimating water demand helps water suppliers and decision-makers avoid waste and shortage by enabling a balance between supply and demand for urban water resources.

This paper presents an analysis of water demand using artificial intelligence. Three machine learning methods have been developed to evaluate the management of water resources. These systems consider several factors such as the community, economics, water demand, and resource availability. The models were trained using a seven-fold CV. Using the test data, the three models were evaluated using the RMSE and R^2 score metrics.

The expected accuracies were better than 90% since the data sets with the same explanatory variables could be utilized to assess water resource management in various contexts.

The study's conclusions will help utilities and municipalities plan water demand, maximize the relationship between supply and demand, and lower the costs related to erratic water scheduling. For this experiment, a relatively minimal amount of data was collected.

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