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Application of Artificial Neural Network Model In Forecasting Water Demand: Case of Kimilili Water Supply Scheme, Kenya.

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Abstract

Potable water treatment and supply systems are designed and constructed to deliver adequate water to meet consumer demand requirements. Consequently, water demand forecasting is essential for the design and operations management of treated water supply systems. Correct prediction of time-varying water demand trends and the critical water demand values determines the extent to which a network can satisfy critical demand and maintain economic efficiency. This study aimed to forecast Kimilili water supply scheme water demand up to 2030. Kimilili water supply scheme being operated by Nzoia Water Services Company Limited is characterized by rapidly increasing water demand leading to persistent water supply shortages hence unplanned fluctuations in the system water production hours. The artificial Neural Network (ANN) model was utilized to forecast Kimilili water supply scheme water demand. The trained model had good performance with a coefficient of determination (R^2) of 0.999972988. The results indicated that Water demand for the Kimilili water supply increased with time, and the general relationship between time and water demand was defined by a sixth-order polynomial function given by $y = 9e\text{-}0x^6 - 1e\text{-}05x^5 + 0.0005x^4 - 0.0115x^3 + 0.1178x^2 + 0.1384x + 100.48$. The study confirmed that ANN could simulate the water demand characteristics of the water supply very well.

Keywords — *Water demand, Artificial neural network, Black box, Sociologic variables, Economic variables.*

I. INTRODUCTION

Potable water supply distribution systems are designed and constructed to convey treated water from the water treatment plant to end-users. The water supply distribution system has to meet two primary requirements; First, it needs to deliver adequate water to meet consumer demand and fire demand requirements. Second, the water system needs to be reliable (availability of the required amount of water 24 hours a day in 365 days a year). According to [1], it is necessary to plan and construct suitable water supply schemes, including well-designed distribution networks, to ensure supply of quality potable water in sufficient quantities to the various users in the community with their demand requirements. Planning and designing of water treatment and supply system for an area is determined by the water demand requirements for the target area to be served. The area water demand needs are usually projected for a certain period for which the water supply system is intended to be in service.

Water usage globally is increasing due to the increase in population and industrialization; thus, forecasting water demand requirements is an important factor for the design and operational demand management of water supply systems. Urban areas' water demand in Kenya is rapidly changing, the population is rapidly increasing due to rural to urban migration, although in a differentiated manner. The water demand is linked to complex interactions that influence it. Water demand for planning and design of supply systems indicates both current and expected water consumption in any given area over the specific time period. While several studies have been conducted in the developed countries to better understand the characteristics of municipal water uses, this may not be the case in the developing countries**.** This knowledge is even less understood in Africa [2]. Generally, water demands vary and consideration of the probabilistic nature of the variations lead to more informed assessments of the performance and reliability of water distribution systems [3].

In order to understand water supply-demand, it is necessary to identify and model the determinants of water demand and investigate the disaggregated pattern of use. Successful water demand forecasting depends on many factors, including understanding the stability of water demand, the availability of essential data, the influences of water demand, and how these influences may change in the future. Collecting data and deciding on the analysis format is critical to developing a reliable and credible model [4].

Some of the developed water demand forecasting methods are based on an analytical or mathematical approach, while others (mainly for short-term forecasting) utilize a purely heuristic approach [5]. Subsequently, some researchers have attempted to integrate mathematical and heuristic approaches for short term water demand forecasts [6]. The simulation models' success results in an improved understanding of the modeled system and a useful predictive tool [7] and [8]. The philosophies of [7] and [8] suggest that the pursuit of forecasting in research areas such as aquatic sciences improves our understanding of forecast modeling. For example, understanding the variables within forecast models enhances the foundation for simulation science.

Water demand forecast models can be classified into five main types, per capita water demand-based model, which involves determining future water needs as per the number of users, it relies on the use of 'unit water demand' coefficients determined per capita or per unit of industrial output, thus also known as unit water demand-based model. The Multivariate Statistical Model method is characterized by estimating the statistical relationship between per capita consumption dictated by a set of explanatory variables, including water tariffs, household size, household income, economic activity, climate, and water policies. Black box (data-driven) model approach whose basis of modeling works on the assumption that demand's future evolution can be deduced from past tendencies. The micro component model approach assesses total consumption by simulating in detail variations in the ways consumers use drinking water. It is also known as 'end use modeling' and is applied majorly for domestic demand forecasting. The composite model approach utilizes hybrid models combining two or more of the four methods described above. This is also the case for water demand forecastings software packages such as Institute for Water Resources Municipal And Industrial Needs (IWR-MAIN). This study utilized the black-box model approach to forecasting water demand for the Kimilili water supply scheme from 2017 to 2030. The water demand is simulated using Artificial Neural Network (ANN) model to determine the water supply system's future water supply based on historic data series calibrated and validated using the ANN model.

II. METHODS

A. Study Area

Kimilili, water supply scheme, lies within 0° 47' 0'' N, 34° 43' 0'' E (UTM Northing: 86621.02 Easting: 691036.93 Zone: 36N) and is managed by Nzoia Water Services Company Limited. The water coverage for the Kimilili water supply scheme is 65%, the mean total precipitation of the area is 1400mm/year, relative humidity is between 65% and 63%, and the average temperature is 24.5 °C. The water for Kimilili water supply is abstracted from River Kibisi via intake works located about 7.5km from Kimilili town, then raw water has gravitated to the water treatment works located at Kamtiong'o through three 150mm, 3.2km long each parallel uPVC class 'D' pipelines. Kamtiong'o Water Treatment works is situated at the foot of Mt. Elgon (N00º 48' 56'') (E34º 42' 10'') and 1755m ASL 4.3Km from Kimilili town. Kimilili water treatment plant has a design capacity of 5000m^3/d, and treated water is stored in a 2500m^3 ground reinforced concrete clear water reservoir then gravitated to Kimilili town via 250mm and 200mm uPVC parallel pipelines. The distribution network amounts to about 87 km in length, and the pipes are a mixture of AC (1.8%), GI (10.2%), and uPVC (88%), [9].

B. Research Design

This research adopted historical design, historical water consumption data, and water loss data to forecast the schemes' water demand.

C. Target population

The study targeted all the varying active water consumer connections consumption trends from 2008 to 2016 mainly categorized into four consumer classes (domestic, commercial, institutional and communal) of the Kimilili water supply scheme.

D. Data

The data utilized in the study comprised mainly of secondary data that was collected from the company records. The data utilized included water connections, water demand, and water losses.

E. Data Collection Instruments

Data were obtained through document review of both billing system and management reports.

F. Data Processing

The monthly data reports for 108 consecutive months (2008 - 2016) for water connections and respective water demand (water billed) per each consumer category were generated from the Kimilili WASANIS billing system and then exported into an excel file then saved. The monthly water loss figures for 2008 - 2016 were obtained from the annual company reports and entered into their respective monthly columns in the saved exported water connections, and water demand excels file generated by the billing system. The updated Excel file was saved in readiness for loading into the water demand forecast model (neural network tool of the MATLAB (R2014a), platform).

G. Data Analysis

Water demand forecasting involved the development of the ANN water demand forecast model using MATLAB (R2014a) software, calibration of the ANN model using the training data subset of 44 consecutive calendar months (Jan 2008 – Aug 2011), validation of the ANN water demand forecast model using the validation data subset of 32 consecutive calendar months (Sep 2011 – April 2014), testing of the ANN water demand forecast model using testing data subset of 32 consecutive calendar months (May 2014 – Dec 2016) and forecasting the water demand of Kimilili water supply scheme network using the developed ANN water demand forecast model for a total of forty-eight consecutive months (January 2017 to December 2020) then extended annual water demand forecast for ten years period (2021 - 2030).

H. Outputs

The main model outputs are water demand and water losses.

I. Performance Evaluation of ANN Model

During calibration and validation of the water forecasting model, it is necessary to assess the model's performance. This is achieved by statistically comparing the model (predicted) values with the observed values using various statistical measures, which include; the Coefficient of Determination (R^2), Root Mean Square Error (RMSE), and Nash-Sutcliffe Efficiency (NSE). This study applied the coefficient of determination method for model calibration.

1) Coefficient of determination (R^2)

The coefficient of determination (R^2) represents the variance percentage in calculated data experienced by the model. The coefficient of determination (R^2) is represented by equation 1.

$$R^2 = \frac{\sum_{i=1}^{n}(O_i - \bar{O})^2}{\sum_{i=1}^{n}(P_i - \bar{O})^2} \tag{1}$$

Pi is predicted value, Oi is observed value, n is number of samples, and Ō is the mean of observed data.

The general performance rating criteria developed by [10] for calibration and validation are given in Table I.

TABLE I. Performance Rating for R^2

Performance rating	R^2
Very Strong Relationship	> 0.8
Strong Relationship	0.6 – 0.79
Moderate Relationship	0.4 – 0.59
Weak Relationship	0.2 – 0.39
Very Weak Relationship	< 0.19

III. RESULTS AND DISCUSSIONS

A. ANN water demand forecast model development

During the ANN model development process, twenty-four network models were developed, out of which network model number 12 was adopted for the study as it produced the best results on testing. The adopted ANN water demand forecast model was recurrent layer type with TRAINLM (Levenberg Marquardt) training function, LEARNGDM (Gradient Descent with Momentum) learning function, MSE (Mean Square Error) performance function, and TANSIG (Tan-Sigmoid) transfer function with three layers and six neurons.

B. ANN Water Demand Forecast Model Calibration

The results for comparison of observed and simulated monthly water demand during the 32 months calibration period (May 2014 – December 2016) is shown in Table II, and Fig.1 Best calibration for the model was attained with a performance of 4.69 at a gradient of 4.2955e-0.005 at epoch 291 with 341 iterations, while the best validation performance achieved was 0.00023942 at epoch 291. A coefficient of determination (*R^2*) of 0.999972988 was attained for testing the performance of the trained ANN model. The R^2 value of 0.99997 indicates a very strong relationship between the observed and simulated water demands. Fig. 2 and Fig. 3 show optimal training and training state results for the adopted MATLAB M12 model.

TABLE II. Observed And Simulated Monthly Water Demands

Months	Observed Water Demand (m^3/h)	Network M12 Predicted Water Demand (m^3/h)	Months	Observed Water Demand (m^3/h)	Network M12 Predicted Water Demand (m^3/h)
May-14	96.36	96.37	Sep-15	98.36	98.37
Jun-14	96.53	96.53	Oct-15	98.53	98.54
Jul-14	96.69	96.70	Nov-15	98.70	98.70
Aug-14	96.83	96.84	Dec-15	98.87	98.90
Sep-14	96.96	96.97	Jan-16	99.08	99.09
Oct-14	97.09	97.10	Feb-16	99.30	99.31
Nov-14	97.23	97.23	Mar-16	99.52	99.53
Dec-14	97.36	97.37	Apr-16	99.74	99.75
Jan-15	97.52	97.53	May-16	99.96	99.98
Feb-15	97.69	97.65	Jun-16	100.19	100.20
Mar-15	97.76	97.77	Jul-16	100.41	100.42
Apr-15	97.84	97.84	Aug-16	100.64	100.65
May-15	97.91	97.91	Sep-16	100.87	100.88
Jun-15	97.98	97.99	Oct-16	101.09	101.11
Jul-15	98.06	98.10	Nov-16	101.32	101.34
Aug-15	98.21	98.21	Dec-16	101.56	101.57

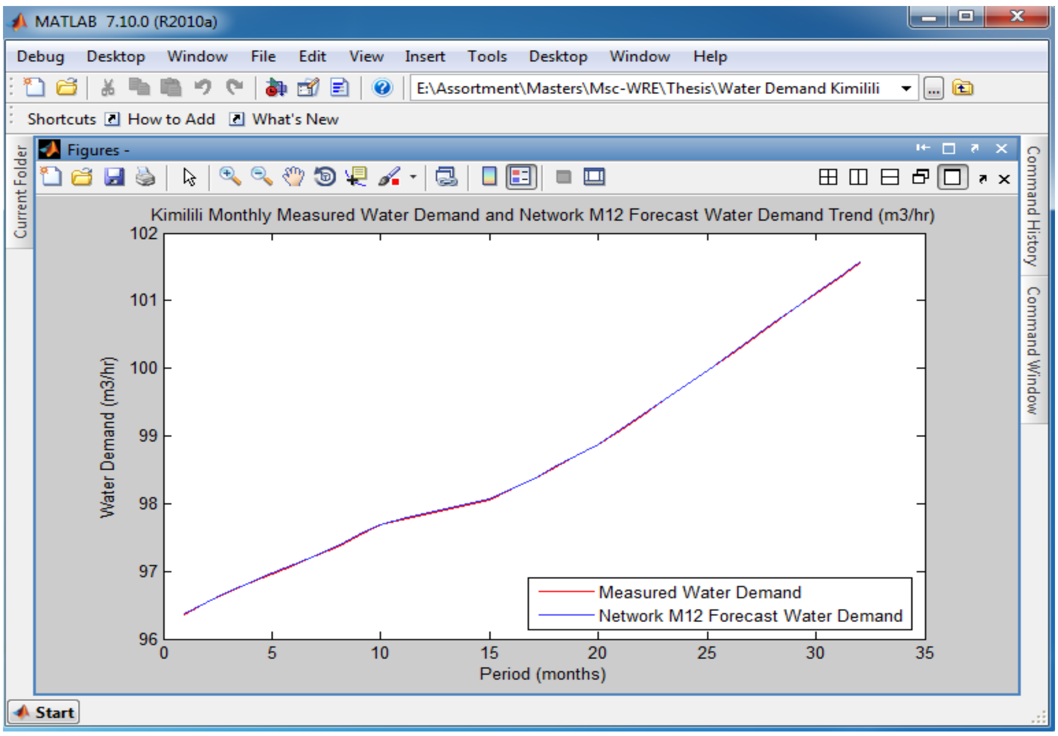

Fig 1: Graphical Relationship Between Observed And Simulated Monthly Water Demands

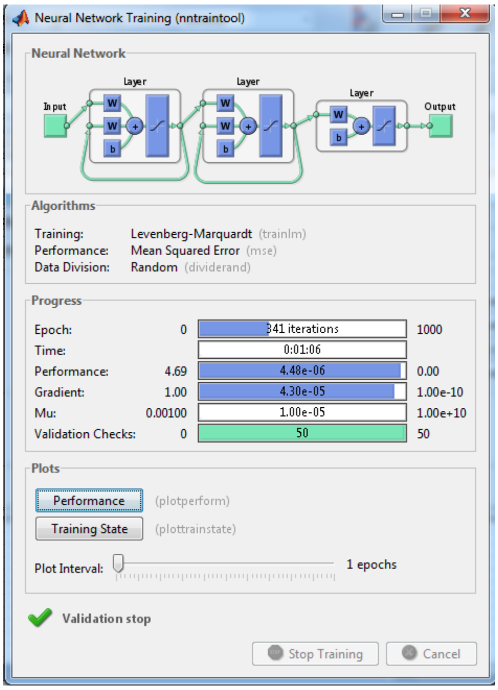

Fig 2: Neural Network M12 Optimal Training.

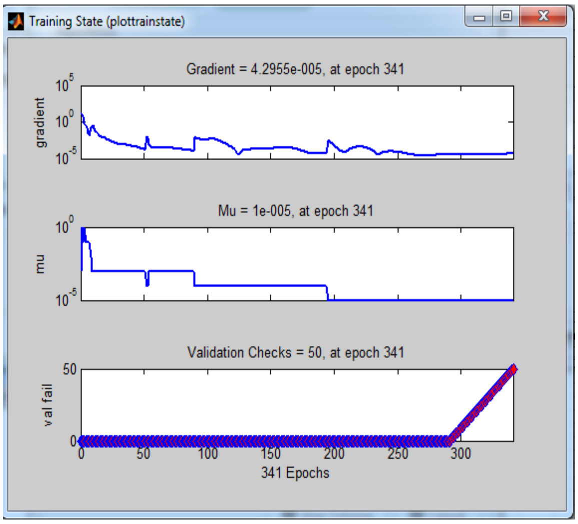

Fig 3: Neural Network M12 Training State

C. Kimilili Water Supply ANN Model water demand forecast

The results for the forty-eight months period forecasted water demand data are as shown in Table III.

TABLE III. Kimilili Water Supply Water Demand Forecast Results (Jan 2017 – Dec 2020)

Months	Demand (m^3/h)	Months	Demand (m^3/h)	Months	Demand (m^3/h)	Months	Demand (m^3/h)
Jan-17	100.19	Jan-18	108.11	Jan-19	118.32	Jan-20	126.39
Feb-17	101.42	Feb-18	109.02	Feb-19	119.42	Feb-20	126.75
Mar-17	102.50	Mar-18	110.30	Mar-19	119.86	Mar-20	126.76
Apr-17	102.53	Apr-18	110.44	Apr-19	120.40	Apr-20	126.32
May-17	102.44	May-18	110.87	May-19	121.20	May-20	125.83
Jun-17	103.24	Jun-18	111.45	Jun-19	121.90	Jun-20	125.87
Jul-17	104.44	Jul-18	112.30	Jul-19	121.98	Jul-20	126.01
Aug-17	104.90	Aug-18	113.50	Aug-19	122.50	Aug-20	126.17
Sep-17	105.65	Sep-18	114.60	Sep-19	123.60	Sep-20	126.50
Oct-17	107.18	Oct-18	115.60	Oct-19	124.40	Oct-20	127.77
Nov-17	107.41	Nov-18	116.40	Nov-19	125.60	Nov-20	129.34
Dec-17	107.91	Dec-18	117.50	Dec-19	126.20	Dec-20	130.55

The results for the ten years extended water demand were as tabulated in Table IV.

Table IV. Kimilili Water Supply Scheme Extended Annual Water Demand Forecast (2021 – 2030)

Year	Demand (m^3/h)	Year	Demand (m^3/h)
2021	138.20	2026	183.56
2022	147.10	2027	200.09
2023	159.30	2028	213.48
2024	166.18	2029	222.55
2025	172.66	2030	228.38

The forecasted water demand trend indicates that by January 2017, the water demand for Kimilili water supply was 100.19m^3/h (27.83 l/s), translating to 2,405$m^{3/}$d, while at the end of the forecasted period (December 2020), the water demand will be 130.55m^3/h (36.26 l/s), translating to a daily water demand of 3,133m^3. Every year, the water demand trend indicates that the demand for water between October and March is generally high, and between April and September, the demand is generally low. This is attributed to the fact that the rains are usually light (low); thus the consumers tend to depend mostly on tap water supplied from the Kimilili system, resulting in high demand. From April to September, the rains are generally high, leading to the consumers having an alternative water source, thus depending less on the tap water from the Kimilili system, consequently leading to low water demand.

From the forecasted water demand data, the best curve of fit drawn using excel for the relationship between the water demand and period indicates that the general relationship between monthly water demand and period (months) is a polynomial function of order six defined by equation 2.

$$y = 9e\text{-}0x^6 - 1e\text{-}05x^5 + 0.0005x^4 - 0.0115x^3 + 0.1178x^2 + 0.1384x + 100.48 \quad (2)$$

Where y is monthly water demand in m^3/hr, x is period in months, and e is the coefficients' standard error value.

The forecasted extended annual water demand trend indicates that by 2021 the average annual water demand for the Kimilili water supply scheme will be 138.20m^3/h (38.39 l/s), translating to 3,316.90$m^{3/}$d, while at the end of the forecasted period (2030), the water demand will be 228.38m^3/h (63.44 l/s), translating to a daily water demand of 5,481.22m^3. From the forecasted extended annual water demand data, a curve was drawn with the best curve of fit using the MATLAB R2014a plot command window's basic fitting tool to establish the relationship between the annual water demand and period (year). It was established that the general relationship between annual water demand and period (year) is a polynomial function of order five defined by equation 3.

$$y = -0.0021x^5 + 22x^4 - 8.7e + 0.4x^3 + 1.8e + 0.8x^2 - 1.8e + 11x + 7.2e + 13 \quad (3)$$

Where y is annual water demand in m^3/hr, x is period in the year, and e is the coefficients' standard error value.

IV. CONCLUSION

The ANN model implemented for the water supply scheme provides a means to assess future water demand trends for Kimilili Water Supply Scheme. The results have proved that the ANN model can simulate the water demand for the Kimilili water supply scheme and thus can be used to simulate other water supply schemes. The study has demonstrated that the general relationship between period (time) and water demand for the Kimilili Water supply scheme is a polynomial function of order six defined as $y = 9e\text{-}0x^6 - 1e\text{-}05x^5 + 0.0005x^4 - 0.0115x^3 + 0.1178x^2 + 0.1384x + 100.48$. Furthermore the general relationship between period and extended annual water demand was a polynomial function of order five defined as $y = -0.0021x^5 + 22x^4 - 8.7e + 0.4x^3 + 1.8e + 0.8x^2 - 1.8e + 11x + 7.2e + 13$.

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