Journal of Theoretical and Applied Information Technology
15th November 2022. Vol.100. No 21

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

PREDICTION FOR NON-REVENUE AND DEMAND OF URBAN WATER USING HYBRID MODELS OF NEURAL NETWORKS AND GENETIC ALGORITHMS

BURHAN FARAH[1], MOHAMMED AWAD[2], AMJAD RUTROT[1]

[1]Department of Computer Science, Arab American University, Palestine
[2]Department of Computer Systems Engineering, Arab American University, Palestine

E-mail: bfarah@qou.edu, mohammed.awad@aaup.edu, amjad.rattrout@aaup.edu

ABSTRACT

Palestine faces continuous struggles in maintaining the proper water supply in the water sector. Therefore, "Non-Revenue water" and supply demands are necessary to reduce the water losses and save the financial resources to strengthen the water sector. To do that we must develop the ideal water usage/loss prediction model to plan the future usage of water. This paper explores and develops AI models that could efficiently predict the water losses and water demands in Palestine, focusing mainly on Beitunia city. Different Artificial Neural Networks (ANNs) with different learning approaches had been used in this paper. The historical and extracted data, representing water supply/consumption in Beitunia are used to propose a nonlinear model. The data is input into the models of ANN and helps predict the water losses/demand in Palestine, to provide a more accurate prediction model. Three models of ANNs were used; Multilayer Perceptron NNs (MLPNNs) MLPNNs-LM, Radial Basis Function NNs (RBFNNs, newrb), and Genetic Algorithms (GAs-MLPNNs). We also used the Autoregressive integrated moving averages (ARIMA) as a linear statistical model to predict water supply using collected data from Beitunia city. The result showed that ANNs models are more efficient than the ARIMA model for the prediction of water movement. Finally, The MLPNNs-LM model results exceeded the other ANNs models in comparison.

Keywords:- *Prediction, Water Losses, Water Demand, Non-Revenue water, Multilayer Perceptron NNs, Radial Basis Function NNs, Genetic Algorithms, ARIMA.*

1. INTRODUCTION

With the rapid population growth in the Arab world, specifically Palestine, we see a recurring situation of water scarcity. The water losses and NRW are the imperative factors affecting the water facilities in the water sectors of Palestine. According to the studies in [1,2], there had been up to a 50% of water loss rate. Internationally, the water sector is considered an important segment of the sustainable development goals which means it's vital to solve the water scarcity problem in Palestine. It is crucial to provide an approach (model) that would assist in the prediction of water losses and demand using AI techniques to ensure a reliable water distribution system. The role of prediction is to extract the associated information related to time series data and utilize that to estimate future values, where the associated information contained in time series data is based on trends and periodicity [2]. To improve the efficiency/accuracy of the time series prediction, some essential models have been proposed in the literature such as ARIMA [4], and ANNs. Including other learning methods that could predict future values by understanding the origin of the data and how it changes over time [5].

Time-series predictions are used to determine the water losses and demands within a time series in municipal areas [3]. Instead of a stochastic form, ARIMA [6] is used to predict future values, in the last years as shown in [7]. ANN AI models have started to appear as robust tools for prediction and modeling [8]. Statistical methods are used to investigate and introduce an AI model that could result in the most accurate predictions of the water resources flow in Palestine. Several of the NNs models including ARIMA (as a linear model), their architectural aspects, and learning rule variations, have been studied to reach a predicting model for the preservation of water. This work focuses on the use of ANNs trained on the archived history of the water loss/demands, to the predictions for the future water

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

loss/demands. The data used for these models have been collected from the Beitunia municipal records and database from 2005-2017.

The supplied/consumption data was converted to produce 78 values, for the total of supplied and consumption water. The data is normalized between 0 and 1 to suit the activation functions of the neural network. The applied models used in this work are MLPNNs, RBFNN-Newrb, GAs-MLPNNs, and ARIMA to produce prediction results for the next future years. Finally, they would be compared to select the most efficient model. This work is organized as follows; in section 2, we show the related work of several proposed approaches. In section 3, we presented the Autoregressive Integrated Moving Average Model (ARIMA). In Section 4, we explained the different ANNs models. In section 5, we presented the proposed applied models for water losses and water demand predictions. In section 6, we illustrated the models' results leading to the final section, where we showed the conclusions of the work.

2. RELATED WORKS

In the literature, machine learning and its techniques are employed to predict and estimate the volume of water losses and water demands. Authors in [9], implemented a model by which it estimates the ratio of NRW using ANNs (based on specific parameters that are affecting the leakages in water distribution systems in Incheon). This model was evaluated using “Scatter plot analyses” (SPA) to determine the best ANNs model. The experiment in this study shows that using the ANNs model produces more accurate predictions of NRW percentage compared to other algorithms such as “Multiple Regression Analysis” (MRA). Furthermore, it has been shown that the accuracy in the ANN model varies depending on the number of neurons in the hidden layer. Therefore, the optimum number of neurons in the ANNs model must be set. Also, the accuracy of the “outlier removal” state was higher than that of the original data used state. For the sake of predicting water demand, authors in [10] generated the RBFNNs model for water demand forecasting, using the Dynamic Clustering Learning (DCL) algorithm to select the center of the cluster. The output charts showed the maximum errors at the end of learning, varying predictive accuracy. The maximum error should not be extremely small; or else, the result of forecasting will be over-fitted and poor.

RBF Neural Networks model has good nonlinear processing and estimation ability. The model features high computing speed, high forecasting accuracy, and appropriate application value. In [11] to forecast deficiency of intensity indicator for water, authors used two ANNs models: the multilayer perceptron and the RBF ANNs, the outcome was RBF ANNs show a lower convergence between the anticipated results and the experimental ones than MLP ANNs; also the result shows that the maximum relative error in MLP ANNs is much lower than RBF ANNs, the results showed the multilayer perceptron can be used to model the failure frequency of water conduits, unlike RBF ANNs which are mostly not recommended for forecasting the failure rate indicator. Time-series algorithms help predict Household water consumption. These algorithms are used quarterly to compare the results of ARIMA with the predictions resulting from ANNs models. The neural network shows that it can generate predictions more accurately; close to the actual data of the testing dataset used in their experiment. It indicated that water demands for residential usage would represent around 18% of the total water demand of the country by 2025 [12]. Similarly, in [13], the authors developed a neural network model of short-term (monthly) and long-term (yearly) water demand prediction for Mecca city in Saudi Arabia exercising historical data of both water production and estimated visitors’ distribution. For monthly and yearly predictions, the result also shows that the neural network predictions perform better than that of a regular econometric model. In [14], the distribution network was investigated to evaluate and audit the levels of NRW in Hebron city. The research results show that the NRW ratio is more than 30%; due to unlawful consumption, inexactness in billing volumes, and incorrect meter readings. To improve and enhance the NRW ratio by reducing the losses in the water network, the research refers to two important issues. The first is that there is no appropriate staff qualified to execute activities for detecting water losses. The second issue regards the provision of appropriate technologies that could help reduce (or stop) water losses. While in [2], research efforts were made to detect and reduce water losses in the water supply networks. Precisely, the author conducted an approach based on tracking and repairing leaks in the supply areas in addition to highlighting the leaks using electro-acoustic techniques. Thus, the research result shows that the number of water leaks in the study area was largely reduced; from 5.6 L/sec to 0.16 L/sec. Another study was conducted in the Gaza Strip which employed the Box-Jenkins model. The result shows that the seasonal model of lag 12 (SARIMA $(1, 1, 1) \times (1, 1, 1)12$) is the best model for predicting. The developed

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

model also shows more accurate predictions. This was shown by comparing the output results against the observed values during this period [15].

In this work besides using Autoregressive integrated moving averages (ARIMA) as a statistical model, we used different ANN models to predict water losses and water demands such as Multilayer Perceptron NNs (MLPNNs) MLPNNs-LM, Radial Basis Function NNs (RBFNNs, newrb), and Genetic Algorithms (GAs-MLPNNs).

3. AUTOREGRESSIVE INTEGRATED MOVING AVERAGES (ARIMA)

ARIMA is a model for statistical analysis of time series to predict future data that emphasizes the analysis of the probability or random properties of the time series itself. ARIMA model is based on the famous Box-Jenkins principle [16, 17], generally, ARIMA is called Box and Jenkins model. Two linear models are largely used in time series, autoregressive (AR), and moving average (MA) [16, 17] models. By bringing these two models together, another model was proposed, called the ARMA. In ARIMA models, a non-stationary time series is performed by applying a restricted difference of data points. The mathematical formulation of the ARIMA(p,d,q) model using lag polynomials [35] is given below in equation 2:

$$\emptyset(\mathrm{L})(1-\mathrm{L})^{d}\, y_t = \theta(\mathrm{L})\varepsilon_t$$

$$\left(1-\sum_{i=1}^{p}\emptyset_i \mathrm{L}^i\right)(1-\mathrm{L})^{d}\, y_{t=}\left(1+\right. \qquad (2)$$

The value of the integer's q, d, and p is greater than or equal to 0. The 2.2 equation to refers the order of the I, AR, and MA of the average model respectively. In the differencing process, we use "d" to control the level. So its value is 1 or 0, when d=1 this is mostly enough the model is ARMA(p,d,q). When the value of d =0, then the model is ARMA(p,q). Specifying (p,d,q) is the first step in estimating the ARIMA model, where p or AR refers to several automatic conditions. Q or MA indicates several moving and intermediate terms and d indicates the number of times that the string must be different to motivate the stationery. In ARIMA the accuracy varies because they represent a linear manner of nonlinear systems.

4. ARTIFICIAL NEURAL NETWORKS

The study of neurobiological systems inspired the development of ANN, which is a network of interconnected units. ANN is based on the simulation of the model to access data of these units for prediction, analysis, or any other treatment of input data. The Neural Networks (NNs) model depends on the learning series of mathematical structures (known as neurons) that are arranged and interconnected to solve sophisticated problems. They could be organized in various forms from simple to more complex structures to form NNs. These networks have shown the capability of solving problems in a wide range of research and application fields. In the field of water prediction, it has been tried for many years to learn how future events could be predicted so that preventive actions could be taken to avoid losses of water resources [18]. ANNs can be introduced in two learning methods: supervised and unsupervised. The supervised ANNs depend on the availability and comparability of their output to the desired output. In this type of ANNs, the final output is found by processing input data through the series of neurons using special activation functions and weights. The outputs of these activation functions are finally summed linearly to achieve the final output. Contrary, unsupervised learning lacks such guidance during the learning process. This type of learning generated output from the NN to the target or desired output is missing. In the learning process in such guidance, fewer environments usually depend on the input data items and the commonly shared feature [18]. Figure 1 demonstrates the general structure of neural networks.

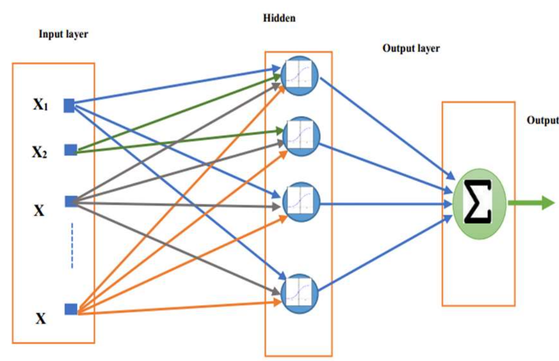

Figure 1: General Structure of an Artificial Neural Network

The neurons contained by the hidden layer determine the action to be made to the input data received from the input layer, the weights of these neurons which are developed by the learning process play a major role in the decision [19]. Later, the data might be

Journal of Theoretical and Applied Information Technology
15th November 2022. Vol.100. No 21

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

transferred to the output layer by applying the activation functions included in the neurons [20].

The data vector X is the data that every neuron gets to process. Every input data has a related estimation of weight W. This esteem is a factor of significance since it updates itself within the training of the neural network with the goal that it shows signs of improvement in conduct. The output of the NN as shown in equation 3 is determined by utilizing the accompanying general equation, which is utilized in most of the supervised kinds of NNs [34].

$$y_{output} = f(\sum_{j=1}^{m} (Xj.Wj + bj)) \quad (3)$$

Where m is the number of inputs, Wj is the related weights vector, Xj is the input vector and bj is the bias. The stimulation function f known also by activation function- is performed at each neuron to generate a non-linear output [21] The general objective of using ANNs in this work is to utilize various types of artificial neural networks (ANNs) and different forms of learning algorithms to produce a computational Intelligence model capable to predict the non-revenue water [NRW] and the actual water demands.

5. THE PROPOSED APPLIED MODELS

For the collected data of Beitunia city, different NNs Models with different learning algorithms will be used to forecast the future values of water demand and water losses NRW. NRW and water demand predictions are performed by applying different types of ANNs models. In our experiment of this research, for NRW and water demand, we produce three prediction models; the first is the MLPNNs model, the second newrb Model using RBFNNs, and a hybrid model using a genetic algorithm with MLPNNs. The data used for the training as well as the testing are viewed as the input data collected from database sources of Beitunia municipality of water consumption and water losses. The main goal of the time series is to build a model to derive future unknown data from current data by minimizing the error between input and output. Data of water demands and water losses were normalized as a range of continuous data between [0 and 1] to fit NNs activation functions that will be used in the applied NNs algorithms in this work as shown in equation 4, where (yi) is the normalized value and (xi) is the real consumption, min and max are the maximum and minimum values for real consumption [22].

$$y_i = \frac{(x_i - (x))}{((x) - (x))} \quad (4)$$

In this work besides applying the ARIMA model, we have also applied three NNs learning algorithms (As shown in figure 2, to evaluate the results generated by the employed NNs models). As we see in figure 2, the process consists of many phases. First, data is stored in Beitunia municipality databases with a different format which is extracted and converted to be suitable to use. Secondly, the data is normalized between 0 and 1 to suit the activation functions of the neural network. Thirdly, we need to verify and validate the models to make sure that these models will forecast values with the lowest difference in the case of regression models to the most needed values possible by using Cross-validation.

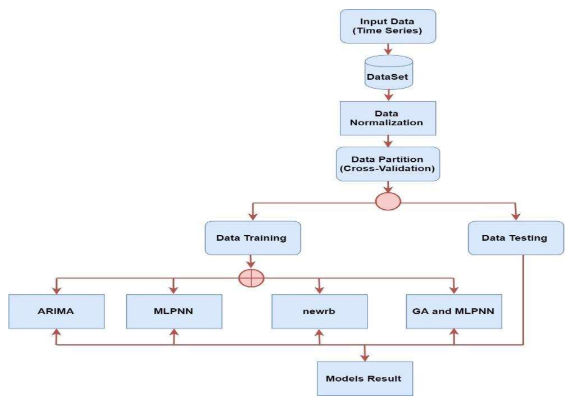

Figure 2: General method procedure flow chart.

Finally, to get the result we apply all models (MLPNNs, RBFNNs, "newrb", GAs-MLPNNs and ARIMA)

5.1 ARIMA Models and Prediction using Box-Jenkins Approach

A time series can be either a linear or non-linear problem depending on the form of the past observations of a series whether it is represented as a linear or non-linear relation. Moreover, ARIMA is composed of autoregressive (AR) with a moving average (MA) method. This hybrid method is integrated with data. It is a key point to select the most fitting model that reflects the underlying structure of the series for future prediction. A time series can be either a linear or non-linear problem depending on the form of the past observations of a series. Moreover, ARIMA is composed of autoregressive (AR) with a moving average (MA) method. This hybrid method is integrated with data of different processes, which is important to make sure that data is being analyzed (represented as data with stationary characteristics). As a result, the combination is called the "Autoregressive Integrated Moving Average" (ARIMA). An autoregressive (AR) model is a representation of a kind of random process, which can represent some time-varying processes as time-series data. The autoregressive model points out the target variables are dependent linearly on their previous values and a randomness term. Hence, the model is in the form of a stochastic difference equation [23]. Suppose that the series (Rt), t =... -1, 0, 1 ... is an evenly spaced feebly on covariance stationary time series or stationary time series, Then the linear model for time series analysis can be expressed as follows:

$$R_t = f_1 R_{t-1} + ... + f_p R_{t-p} + e_t - q_1 e_{t-1} - ... - q_q e_{t-q} \quad (5)$$

Where f's are the autoregressive parameters to be estimated, the θ's are the moving average parameters to be estimated, the R's are the original series, and the e_t is a series of unknown random errors (white noise) which are assumed to follow the normal probability distribution. (Rt) is a mixed "autoregressive moving average process of orders p and q and referred to simply as ARMA (p, q). For the general ARMA(p, q) model, we say that εt, is independent of Rt−1, Rt−2, Rt−3,…, a stationary solution for the equation (6) the stationary solution exists if and only if l roots of the AR characteristic equation, (x) = 0 are outside the unit circle [34]. For determinism, we have to assume that the roots of θ (x) = 0 are outside the unit circle. Where (εt) is a sequence of uncorrelated variables, it is also referred to as a white noise process, and $(f_1,, f_p, \theta_1, .., \theta_q)$ are unknown constants or parameters. The Box-Jenkins model can then be expressed as the following equation:

$$(1 - \varphi_1 B - \varphi_2 B^2 - \ldots - \varphi_p B^p) R_t = (1 + \theta_1 B + \theta_2 B^2 + \ldots + \theta_q B^q) \varepsilon_t \quad (6)$$

Where B is the backshift operator, that is BXt = Xt−1

$$\varphi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \ldots - \varphi_p B^p \quad (7)$$

$$\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \ldots + \theta q B^q \quad (8)$$

In general, the ARMA (p,q) is a combination of an AR(p), and a MA(q), and it can be written as follow:

$$R_t = \sum_{i=1}^{p} \emptyset_i R_{t-i} + \sum_{i=1}^{q} I \, \varepsilon t_{-i} \quad (9)$$

In reality, it is often challenging to apply an ARMA model directly to a specified time series; this is because of its nonstationary features, it also requires a transformative process. Usually, this is the case that the time series of differences is stationary despite the nonstationary of the basic process. This leads to the application of the (ARIMA) model.

This series has a hybrid solution that is Autoregressive and moving on average, which resulted in a very general time series model [23]. The method of predicting water losses and demand using Box-Jenkins is as follows: Firstly, the prediction cycle starts with the identification of the data model using ARIMA. This helps determine the order of differencing required to produce a stationary time series. Secondly, we identify the value of p (AR) and q (MA) components for both seasonal/non-seasonal series. While developing the ARIMA model, the analysis of the autocorrelation function (ACF) and partial autocorrelation function (PACF) are required to be performed. These are obtained by plotting the original series in addition to the ACF and PACF. At this point, it is required to estimate the parameter for the chosen ARIMA model by using the data to train the parameters of the model. For validation, the model diagnostics (residual) checking must be developed. The diagnostic identifies whether the residuals from the model are independent and normally distributed. The residual is the difference between the observed value and the predicted one of the quantities of interest. The residual should be uncorrelated; resulting in zero means and zero variance as well. Afterward, the prediction and error-checking stage can be performed.

5.2 Multilayer Perceptron Neural Networks (MLPNNs) Model

MLPNNs can predict every time series function by tuning the network with appropriate hidden layers of structure and a suitable number of neurons. Also, ANNs have a good characteristic of solving such complex problems so the training process maps the outline between the input and output data of the NNs. When the input patterns are provided to the NNs with initial weights, the output of the NNs is given by the following equation: [20]

$$y_i = f\left(\sum_{j=1}^{m} w_{ij} x_j + b_i\right) \quad (10)$$

Where Wij is the connection of the weight, Xj is the value of the ith inputs for simple NNs, bi is the bias, m is the number of neurons and f is the activation function. MLPNNss is a time series prediction model, which is impossible to use and find a single

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

configuration for each application. The choice of training patterns that are performed is reliant on the explicit needs of the prediction, which will show in the output and the quality of information available. Any changes in the patterns of training would require different training parameters for the NNs, but the training process remains the same [25, 26].

Multilayer feedforward with backpropagation neural networks (MFFNNBP) is an MLPNN that passes the inputs and the weights from one layer to the next one through the feed-forward process. Then it performs the weights update to be back-propagated to the previous layers to recalculate the weights [26].

$$\text{output} = f^2 \left(\sum_{j=1}^{n} output_1 . W_{jk}\right) \qquad (11)$$

Our proposed ANNs architecture is reliant on the NRW and water demand regression for the year "2018" using historical data of losses and consumption in Beitunia city. In MLPNNs, the output of a layer will be an input for the next layer passing from the input layer to the output layer; f1 is the sigmoid activation function [26]. The equation used for the output is shown as in the following equation 11:
Where the output of the first hidden layer (output1) is calculated using the following equation 12:

$$\text{output}_1 = f^1 \left(\sum_{j=1}^{n} in_i . W_{ij}\right) \qquad (12)$$

Where f1 and f2 are the activation functions for both the output layer and hidden layer that calculated as in equations 13 and 14:

$$f^1 = \frac{1}{1 + e^{-X}} \qquad (13)$$

$$f^2 = X \qquad (14)$$

Where x is the input vector. Depending on equations 13 and 14, weights are updated use equation the following equation 15:

$$\Delta w_{jk}^{n} = -\mu \frac{dE(w_{jk}^{n})}{dw_{jk}} \qquad (15)$$

µ is the learning rate with a value between 0 and 1. The final output depends on all earlier layers' output, weights, and the algorithm of learning used [27].

The backpropagation process calculates the gradient proper error between the desired and the predicted output by looking at the new weights each time. The back-Propagation step used to update the weights depends on the calculation of the gradient descent error between the target output and the predicted output considering the new weights. In this thesis, we use Levenberg Marquardt Algorithm (LM) [28], which trains the NNs and reduces the prediction error values by adjusting and updating the weights. LM converges according to the steepest descent methods with better generalization. The proposed model in this work using Multilayer Perceptron NN Back Propagation NN is illustrated in the following steps.

Step 1: Load Data (time-series data of water losses and demands)
Step 2: Initialize MLPNNs
- Normalize Input and Target data
- Divide the dataset into two parts; training and testing (using cross-validation)
- Set initial Neuron number
- Initialize the Network Weights w randomly
- Initialize Network Bias b randomly

Step 3: Start Training Phase
- Predict
- Read output
- Calculate MSE
- **While** MSE <= threshold Do:
    - Calculate ΔW for all weights from the output layer to the hidden layer
    - Calculate ΔW for all weights from the hidden layer to the input layer
    - Update the *W*eights of the network
    - Predict
    - Calculate MSE Error between Predicted and Target outputs
- Record training MSE.

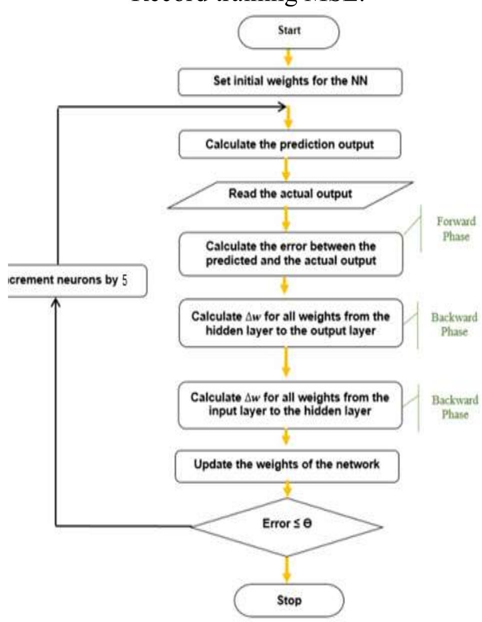

Figure. 3: The proposed MLPNNs model pseudo code

Step 4: Start Testing Phase

- Calculate Predicted output using
  - Testing data based on the generated model from Step 3.
- Calculate testing MSE.

Figure 3 illustrates the proposed MLPNNs model that uses the Levenberg-Marquardt training algorithm (LM), adjusted for the water demand and water losses prediction process.

5.3 Proposed RBFNNS Model Methodology

RBFNNs were used for function approximation and time series prediction, in this work it is used for time series prediction of water losses and water demands.

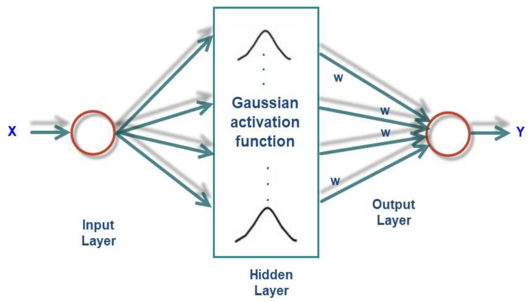

Figure.4: RBFNNs general Architecture of three layers

The significance of the usage of such a method is to cluster dataset points around a set of popular highlighted points called centers. These points (center) are grouped to the centers based on another parameter for the RBF network which is called radii (r); which agrees to the distances for each input data point to the center points of each cluster (or group) [29]. Figure 4 shows the general form of Radial Basis Function Neural

We have used newrb which was included in the Matlab toolbox as a standard training algorithm for RBFNNs neural network, to compare with ARIMA, MLPNNs, and GA-MLPNNs. newrb repetitively creates a radial basis network by using one neuron at a time. Neurons are added to the network until the sum squared error falls beneath an error goal or a maximum number of neurons has been reached. The used newrb function is expressed as follows: *net = newrb (Xt, Tt, Goal, Spread, M_N),* where Xt is the input vectors, Tt is the target vectors and M_N is the maximum number of neurons. In *newrb*, each iteration of the input vector which leads to reducing the network error is most used to create *radbas* neurons. Then the new error is verified, and if it is small enough then the *newrb* is stopped. Else, the subsequent neurons are added. This process is repeated until two conditions are achieved, first if the target of the error is achieved, second if the number of neurons is reached to the maximum. In *newrb*, it is significant that the spread is sufficiently large that the *radbas* neurons react to overlapping regions of the input space, however, the value of spread shouldn't be so large that all the neurons react in essentially the same way [30].

To predict the water losses and water demands, we have collected actual data of water demands and water losses from Beitunia city, for this goal *newrb* Matlab function was used to train the RBFNNs. Newrb function creates an RBFNNs used for function approximation, where the new neuron is being added to realize the determined error or to realize the best fit, in general, and depending on *newrb* used in Matlab, the function newrb repetitively creates a radial basis network one neuron at a time. Neurons are added to the network till the sum of squared error falls under an error goal or the maximum number of neurons was gotten, this model has the number of steps illustrated in the following pseudocode.

RBFNNs-Newrb Model

Step1: *Initialize newrb model parameters:*
Net = newrb (I, T, goal, spread, M_N, N);
I: input vectors.

- *T: target vectors.*
- *Goal: Mean squared error (MSE) goal (default value = 0.0)*
- *Spread: Spread of RBF (default = 1.0)*
- *M_N: Represents the maximum number of neurons (Q is the default value)*
- *N: Represents the number of neurons to add (25 is the default value)*

Step2: *Train the system using the parameters (I, T, goal, spread, M_N, N)*
Step3: *If the training process finds the Goal stop and return the RBFNN Architecture*
Else go to ***Step2***

In RBFNNs, the newrb relies on spread value; when using the too large value of spread that means requiring a lot of neurons to fit the fast-changing function, on the other hand using too small a value of spread means requiring a lot of neurons to fit a smooth function, and the RBFNNs perhaps do not popularize well [31].

5.4 MLPNNs with Genetic Algorithms Model

It is difficult to select the best parameters in NNs for the training process, so it is possible that the results of the training are unacceptable or sometimes bad and this is not because the data is complex or noisy or the algorithm used in the training is weak, but this is due to the failure selecting of the parameters. Therefore, the process of selecting the appropriate parameters increases the success of the training process, and also, enhances the accuracy of ANNs [32]. In general, the training process using MLP can be improved by selecting the Optimum parameters such as the number of neutrons in the hidden layers and initial weights. So, we need such a method to solve this problem, therefore, the optimization process can be implemented using the GAs. In this work, we will focus on using GAs to optimize the network weights to use them in the MLPNNs algorithm to perform the forecasting of water losses and water demands.

The GAs is a stochastic optimization approach depending on the features of natural selection and biological evolution. It is better than other optimization algorithms and it has various advantages over them. GAs can be used to solve and optimize continuous and discrete issues. It is less probable to get trapped in local minima [33] if it is compared with other algorithms such as Backpropagation (BP). The idea behind GAs came from population genetics. It has been used mostly as function optimizer and it has been proved to be an efficient optimization algorithm, particularly for multi-model and non-continuous functions. The GAs develops a population of individuals. GAs uses every individual Yj (j = 1,2,3, , n((n , represents the population size) of population "Y" in order to solve the problem. Individuals are typically represented by strings and each element of which is called a gene. The value of a gene typically rage from (0 to 1). The GAs is qualified for optimizing the fitness function F(.) for every individual of the population. The main steps of the proposed hybrid algorithm are depicted in the following pseudocode.

GAs-MLPNNs Model

Start MLPNNs

Step 1: Load Data

Step 2: Initialize MLPNNs

- Dividing the dataset into two parts training and testing part using cross-validation
- Set initial Neuron number
- Initialize the Network Weights W randomly
- Initialize Network Bias b randomly

Step 3: Start Forward Training Phase

Perform the following steps for every iteration

- Calculate the prediction output using the sigmoid activation function
- Calculate MSE Error between Predicted and Target outputs
- Is the error value <= threshold value?
- Yes: stop and get the MSE and output predicted the value
- No: go to the next step (step 4) to optimize the weight to reduce the error value

Step 4: Start GAs

1) Initialize the population using weights generated in Step 3
2) Evaluate the fitness *f(x)* of each chromosome *x (*weight*)*
3) Carry out the following steps to get the new population:
   a) **Selection**: Select two parent chromosomes for mating depending on the fitness of the chromosomes. Chromosomes that have the best fitness will have the biggest chance to be the new parent.
   b) **Crossover**: Merge the genotypes of two selected parents to produce two new children. The produced children chromosome that has genetic material from both parents
   c) **Mutation**: Spontaneously changes one or more alleles of the genotype. Genetic material is randomly altered to insert new genetic material into the population
   d) **Compare**: All the previous and current best individuals (weights) are added to the population.
   e) Move the next population to the current population to ready the algorithm for the next run.
   f) Evaluate the fitness *f(x)*
4) Get the Optimized weight
5) Calculate the MSE
6) Get the output predicted value

Step 5: Start Testing Phase

- Set Network Weights to be computed in the training phase
- Calculate Predicted output using testing data
- Calculate MSE

6. RESULTS AND DISCUSSION

In this research, experiments have been carried out to check and validate the developed predictive model. Different technologies and frameworks are applied to achieve the objectives of our study. For

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

example, the models were designed and simulated using MATLAB 14a and EViews for the ARIMA model under Windows 10 Intel Core (TM) i7-5600U, CPU @ 2.60GHz, 16GB RAM. The results of conducted experiments will be presented in addition to performing comparisons among different ANN and learning algorithms employed for the goal of our research; water demands and water losses predictions. In the first model, we applied MLPNNs, then, we used the newrb model, and, finally, we experienced GAs-MLPNNs as a hybrid model, besides using the statistical model ARIMA.

6.1 Arima (Box-Jenkins) Prediction Model

6.1.1 ARIMA NRW Result

From the result in Table 1 ARIMA model can't be used for water loss data. In such a case, as we did, we usually fit what's known as the "intervention model".

Table 1: MSE of NRW Using ARIMA Intervention Model

MSE $_{Training}$	MSE $_{Testing}$
1.45E-01	2.23E-01

The intervention model, based on MSE Error values (training and testing) depicted in the table, we can say that the intervention model did not produce a good enough result for the future prediction of water losses. Furthermore, figure 7 illustrates graphically the comparison between the actual and prediction value according to the ARIMA intervention model based on EViews.

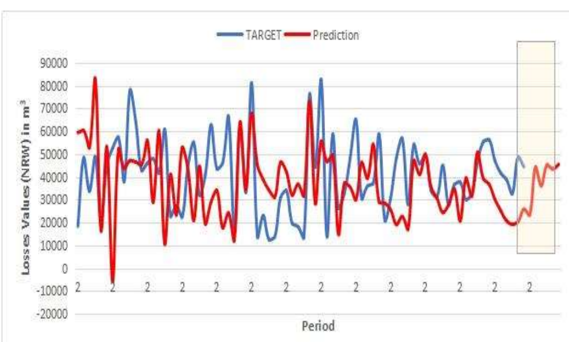

Figure 5: Actual and Predicted Losses Values Using ARIMA

Also, as shown in figure 5, we forecast future quantities of water losses for 6 periods (12 months) of the year 2018 as illustrated in the highlighted area in the graph, later we will use this result to compare with ANN models.

6.1.2 ARIMA DEMAND Result

The unit root test shows that the water demands data is nonstationary and this fact implies the necessity to use the first difference from data. So, we apply the correlogram of the first difference to identify the MA and AR terms, ACF is negative at lag 3 MA(3) and the PACF has a negative value at lag 3 and does not have a positive lag value. The third lag autocorrelation is statistically significant while all following autocorrelations are not. So, we will reduce the difference and the MA levels by one so the fitting ARIMA model will be ARIMA (0,1,2). Table 2 shows the Mean Square Error of the ARIMA model after selecting the best model (0,1,2). Furthermore, according to these values of MSE, we can see that ARIMA (0,1,2) model gives a good result so we can use it in water demands prediction Additionally, using the best model, ARIMA (0,1,2) as shown in the highlighted area in figure 6, we forecast future quantities of water losses for 6 periods of the year 2018.

Table 2: MSE Of Demands Using ARIMA.

MSE $_{Training}$	MSE $_{Testing}$
9.12E-02	1.17E-01

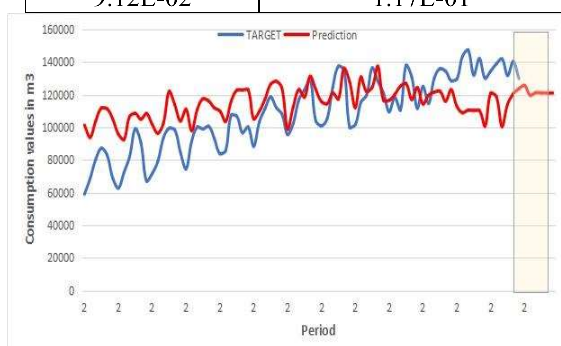

Figure. 6: Actual and Predicted Demands Values Using ARIMA.

As shown in figure 6, and table 2, it's obvious that the proposed model gives some good results based on the values of MSE testing and training, which leads that the model is appropriate in such cases as water loss prediction.

6.2 MLPNNs-LM Prediction Model

6.2.1 NRW Prediction.

All predictions resulting from applying the MLPNNs model of water losses (NRW) are illustrated for Beitunia city. In experiencing different models to select the best one, table 1 and diagram 12 show the best results in predicting water losses of data that were preprocessed prior. The table shows the Mean Square Error (MSE) calculations, several iterations, and the number of neurons; ranging from

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

5 to 90 neurons, with an incremental step of 5 neurons.

Table3: MLPNNs-LM NRW Prediction.

Number of Neurons	MSE Training	MSE Testing	Number of Iteration
5	3.909E-02	7.108E-02	12
10	3.019E-02	1.140E-01	11
15	2.369E-02	1.111E-01	8
20	2.681E-02	1.567E-01	13
25	1.784E-02	1.520E-01	7
30	2.263E-02	1.083E-01	7
35	1.715E-02	1.401E-01	7
40	9.971E-03	2.636E-01	8
45	1.987E-03	2.897E-01	14
50	2.126E-03	2.288E-01	10
55	1.027E-02	2.387E-01	7
60	9.826E-03	2.183E-01	7
65	**6.17E-07**	2.75E-01	6
70	8.208E-03	2.054E-01	7
75	5.772E-05	1.592E-01	9
80	4.370E-03	1.609E-01	5
85	3.885E-03	1.855E-01	4
90	3.613E-03	3.985E-01	4

According to table 3 and figure 7, it can be seen that MLPNNs-LM produces a good result of NRW Prediction; by neuron 65, the model achieves the best (lowest) MSE training of value 6.17E-07 this value can be viewed as small which results in high quality of prediction for the future of water losses. Having presented the model results, it can be noticed that the prediction process is not highly dependent on the number of iterations of the MLPNNs-LM. For instance, with the number of neurons = 45, the process duration is 14 iterations which achieved an MSE value acknowledged by 1.987E-03, which is not a good fit compared to the previous values. One other observation is that the increase in the number of neurons does not necessarily generate more reasonable predictions (least error metrics). We can see the comparison produced by the MLPNNs-LM model between the real and predicted water losses up to the year 2017, also the figure shows the predicted water loss values for the year 2018 as shown in the highlighted area in the graph.
Such results are shown in table 3, which shows that the model is one of the promising models for the future forecasting of water losses.

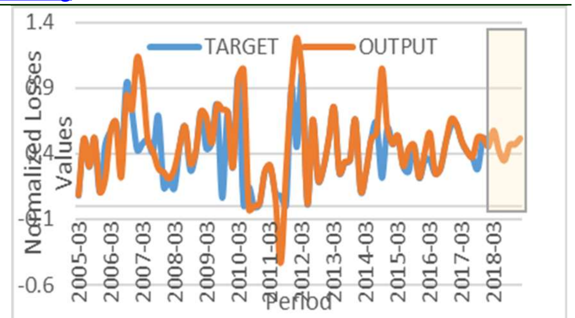

Figure 7: Comparison Between Real and Predicted WaterLoss Values When The Number Of Neurons = 65.

6.2.2 MLPNNs-LM Water Demand Prediction

Table 4 and figure 8 also show that MLPNNs-LM produces highly accurate results in the forecasting of water demand. As seen, the best model is achieved with the number of neurons = 70, by which the MSE obtained is 2.94E-05. As we mentioned before the prediction process does not depend on the number of iterations, although we have 26 iterations with neuron 15, the captured MSE value is 4.87E-03 which could be not acceptable compared to the result of neutron number 70.

Table 4: MLPNNs-LM Demand Prediction.

Number of Neurons	*MSE* Training	*MSE* Testing	Number of Iteration
5	1.06E-02	2.32E-02	22
10	8.69E-03	2.37E-02	8
15	4.87E-03	2.92E-02	26
20	5.20E-03	1.88E-02	10
25	2.45E-03	8.75E-03	14
30	8.31E-04	1.74E-02	10
35	2.82E-04	1.98E-03	12
40	1.29E-03	1.06E-01	8
45	2.87E-04	8.92E-02	11
50	1.46E-04	2.89E-02	15
55	4.69E-04	3.54E-02	9
60	8.88E-05	7.29E-02	7
65	7.30E-04	1.77E-01	7
70	**2.94E-05**	7.25E-02	7
75	3.88E-05	1.00E-01	5
80	6.43E-05	6.61E-02	6

Journal of Theoretical and Applied Information Technology
15th November 2022. Vol.100. No 21

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

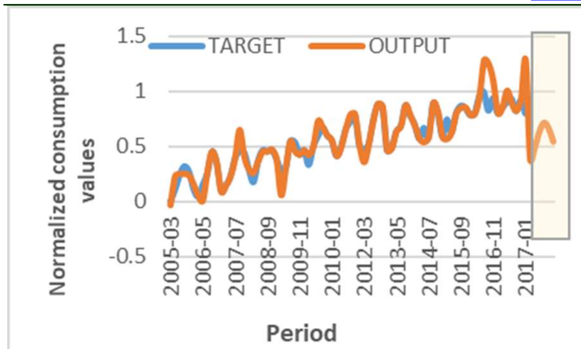

Figure.8: Comparison Between Real And Predicted Water Consumption Values When The Number Of Neurons = 70.

In figure 8, we can see the comparison produced by the MLPNNs-LM model between the real quantities of water consumption and the prediction values according to the adopted model, it is noticeable that there is a convergence in the results indicating the accuracy of the used model Moreover, we predicted water demands values for the year 2018 as shown in the highlighted area in the figure

6.3 RBFNNS Prediction Model

To predict water losses and water demands, we applied a proposed model using RBFNN (newrb) fed by real water losses and water consumption quantities of Beitunia city. In the following sections, we will show the result of the RBFNNs (newrb) model of water losses (NRW) for Beitunia city.

6.3.1 RBFNNS Prediction Model for Water Losses

Table 5:Newrb NRW Prediction.

Number of Neurons	MSE Training	MSE Testing
5	4.43E-02	6.26E-02
10	3.87E-02	7.31E-02
15	3.45E-02	8.77E-02
20	3.13E-02	8.74E-02
25	2.79E-02	8.35E-02
30	2.51E-02	8.44E-02
35	2.34E-02	8.46E-02
40	2.18E-02	8.44E-02
45	2.01E-02	8.59E-02
50	1.71E-02	8.48E-02
55	1.27E-02	8.19E-02
60	5.50E-03	9.35E-02
65	3.78E-03	9.41E-02
70	**2.62E-03**	9.83E-02

In this section, the table and diagrams show the best performance results of applying the proposed model for water losses. The tables below show the MSE (training and testing) values, and the number of neurons used in the experiment; ranging from 5 to 70 neurons, with an incremental step of 5 neurons. According to table 5 and figure 9, we can see the behavior of the proposed model in the forecasting process of the nonlinear time series. It can be seen how the newrb model can perform well; achieving fair results for the prediction of water losses. That is, increasing the number of neurons showed more accurate values, the model finished with an MSE of 0.00262 when the number of neurons = 70 in the hidden layer. Moreover, from the graph in figure 11, we can see the comparison produced by the newrb model between the actual and predicted water loss values (NRW), also the figure shows the predicted water loss values for the year 2018 as illustrated in the highlighted area in the figure.

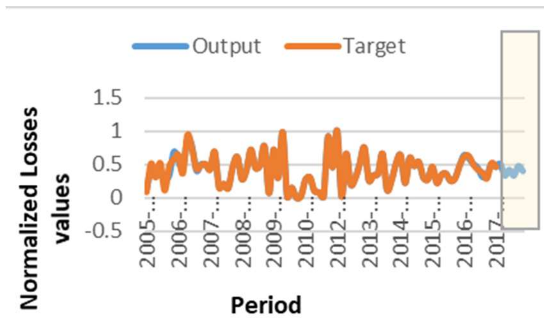

Figure.9: Newrb Best NRW Prediction Result For The Year When The Number of Neurons = 70.

6.3.2 RBFNNS Prediction Model for Water Demands.

In the following sections, we will show the result of the RBFNNs (newrb) model of water demands of Beitunia city In table 6 and figure 12, we can see that the behavior of the newrb model with an error goal of (0.001) in the forecasting process of the nonlinear time series. It is clear that the proposed model converges to the optimum value when the number of neurons equal 50 with better prediction error; the proposed approach performs very well. From Figure 10, we notice the low difference between the actual

Table 6: Newrb Water Demands Prediction.

Number of Neurons	MSE Training	MSE Testing
5	2.55E-02	7.97E-02
10	1.26E-02	1.01E-01
15	1.15E-02	1.15E-01
20	9.26E-03	1.20E-01
25	7.49E-03	1.23E-01
30	3.63E-03	1.21E-01
35	2.58E-03	1.21E-01
40	2.16E-03	1.22E-01
45	2.05E-03	1.22E-01
50	**1.66E-03**	1.22E-01

consumption of water and the predicted values. Also, the figure shows the predicted future values of water demands in the year 2018 as illustrated in the highlighted area.

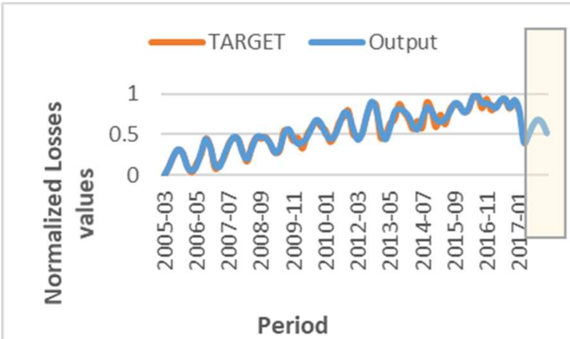

Figure.10: Newrb Best Water Demand Prediction Result For The Year 2018 When The Number Of Neurons = 50.

As shown in figure 10 and table 6, the newrb model can predict water demands for the year 2018 with good accuracy. Also, the newrb model gives a good result based on the values of MSE testing and training, which leads to the model being appropriate in such cases of water demands prediction.

6.4 GAs-MLPNNs Prediction Model

6.4.1 Water Loss Prediction.

Table 7: GAs-MLPNNs NRW Prediction.

N of Neurons	$MSE_{Training}$	$MSE_{Testing}$
5	4.32E-02	6.22E-02
10	3.80E-02	4.60E-02
15	3.76E-02	6.20E-02
20	3.62E-02	6.11E-02
25	3.47E-02	7.80E-02
30	2.79E-02	1.31E-01
35	2.51E-02	1.81E-01
40	2.67E-02	1.11E-01
45	2.22E-02	1.56E-01
50	2.60E-02	1.56E-01
55	2.31E-02	1.74E-01
60	1.85E-02	2.08E-01
65	**1.73E-02**	2.02E-01
70	1.80E-02	3.47E-01
75	1.92E-02	2.02E-01
80	1.81E-02	2.16E-01

As shown in figure 11 and table 7, while the number of neurons increases, the model performs with fewer MSE values. The best result was achieved with several neurons = 65 with a value (0.0173). However, the model shows that the model does not perform well with neurons number more than 65; that is, the MSE value increases with more than 65 neurons. By using the graph and as illustrated in figure 11, we can see a good comparison result produced by the GAs-MLPNNs model between the real quantities of water losses and the prediction values according to the adopted model. Moreover, in this model, we predicted water loss values for the year 2018 as depicted in the highlighted area in the figure.

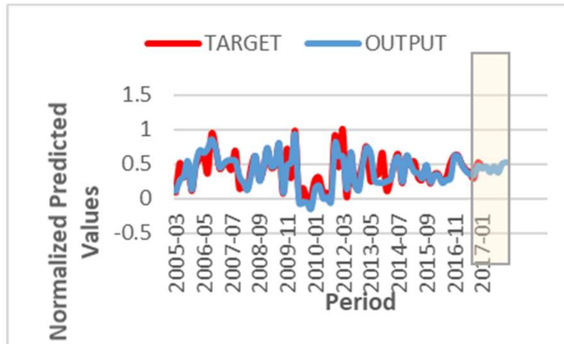

Figure.11: GAs-MLPNNs NRW Prediction Result For The Year 2018 When The Number Of Neurons = 65.

6.4.2 GAs-MLPNNS Prediction for Water Demands

In the following section, we will discuss the result of the GAs-MLPNNs model for water demands. Water Demand Prediction Result as illustrated in table 8 and figure 14 shows that the proposed GAs-MLPNNs model produces accurate predictions with fewer MSE values, which leads that the model is highly appropriate in such cases of water demands prediction. The error was at the minimum of its values (0.0023) when the network was built with several neurons = 55

Table 8: GAs-MLPNNs NRW Prediction.

N of Neurons	$MSE_{Training}$	$MSE_{Testing}$
5	1.14E-02	2.34E-02
10	1.12E-02	8.50E-02
15	8.00E-03	7.22E-02
20	7.50E-03	2.02E-02
25	4.20E-03	5.43E-02
30	3.60E-03	4.53E-02
35	3.80E-03	2.07E-01
40	3.20E-03	7.67E-02
45	3.00E-03	1.39E-01
50	4.90E-03	2.40E-01
55	**2.30E-03**	1.76E-01
60	3.60E-03	3.51E-01
65	6.80E-03	1.45E-01
70	5.90E-03	2.56E-01

Furthermore, in this model, we have produced the predicted values of water demand for the year 2018 as illustrated in the highlighted area in figure 12. Also, the figure shows a good comparison result between real and predicted water consumption.

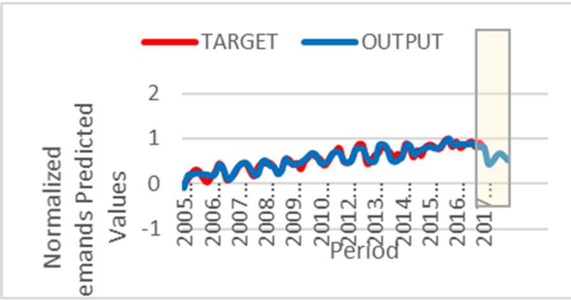

Figure 12: GAs-MLPNNs Demands Prediction Result For The Year 2018 When The Number Of Neurons = 55.

6.5 Comparison and Discussion

In this section, we show a complete comparison depending on the performance from the viewpoint of the error value against the number of neurons employed of all the results obtained for NN models used in this thesis for NRW and water demands for Beitunia city.

E.1 COMPARISON OF WATER LOSSES (NRW)

Figure 15 presents the error values and the number of neurons for the three Models; MLPNNs-LM, newrb, and GAs-MLPNNs to observe the performance of each built network using the mentioned models. The supremacy of the MLPNNs-LM model can be seen in overall models and this has been shown from the first Neuron (5) to the last one approximately. It can also be seen that the newrb model performs better than the GAs-MLPNNs model.

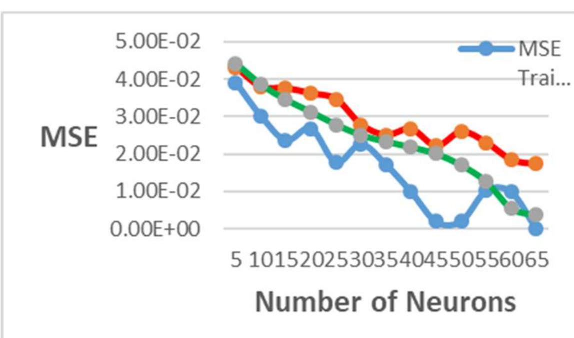

Figure.13: MSE Result Values Of NRW For The Three Models.

Error-values are displayed in Figure 13 with specific neurons for the three Models; MLPNNs-LM, newrb, and GAs-MLPNNs, it is noticed that there is a fluctuation in behavior with an advantage to the MLPNNs model overall at the end of the prediction experiments

6.5.1 Comparison of Water Demands

Figure 14 shows the Error values and specific numbers of neurons for the three Models; MLPNNs-LM, newrb, and GAs-MLPNNs, it is noticed that there is a fluctuation in behavior with an advantage to the MLPNNs-LM model overall at the end of the prediction experiments.

We present a comparison of all the results obtained for the NN models used in this thesis. The following two tables (table 8 and table 9) show the best MSE values for both water losses (NRW) and water demands.

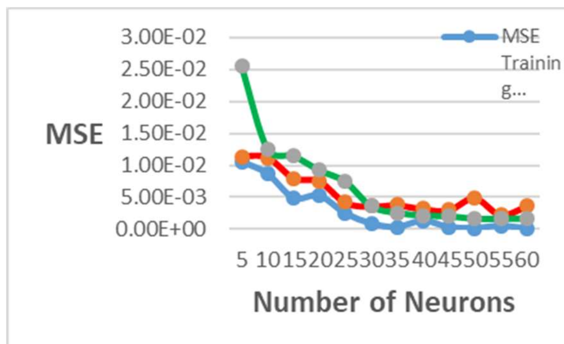

Figure.14: MSE Result Values of Water Demands Prediction For The Three Models.

Table 9: Comparison of MSE For The Four Models Of NRW.

	MLPNNs-LM	Newrb	GAs-MLPNNs	ARIMA
Neuron	65	70	65	-
MSE	6.17E-07	2.62E-03	1.73E-02	1.45E-01

Table 9 shows the best MSE performance values of the function produced by all models MLPNNs, newrb, and GAs-MLPNNs which have been applied for the water losses (NRW) prediction. While Table 10 shows the best MSE performance values of the function produced by all models MLPNNS, newrb, and GAs-MLPNNs which have been experienced for the water demands prediction

Table 10: Comparison Of MSE For The Four Models Of Water Demands.

	MLPNNs	Newrb	GAs-	ARIMA

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

	-LM		MLPNNs	
Neuron	70	50	55	-
MSE	2.94E-05	1.66E-03	2.30E-03	9.12E-02

Results depicted in tables 8 and 9 of water losses (NRW) and water demands show the achievement of the best performance with the MSE values produced by MLPNNs, newrb, GAs-MLPNNs, and ARIMA models. According to the MSE values observed, it can be noticed that the MLPNNs model outperforms the others in terms of the forecasting of water losses and demands. While the newrb model is the second-best model, which performs better than the hybrid GAs-MLPNNs model. On the other hand, the statistical model achieves the worst performance in terms of MSE values when compared to the rest of the models experienced in this study, this is because the ARIMA model relies on linear data to be accurate.

7. CONCLUSIONS

Water loss problems concerning the Palestinian municipalities and water utilities have led to some disruptions of services, in addition to affecting the quality of water distribution services. The historical data of water loss and consumption quantities from the Beitunia database were used from models between 2005 and 2017. It can be seen that the data changed over a series of times. After several modeling iterations, ANNs models can be fitted better than the ARIMA model for the prediction of water demand and water losses. While the MLPNNs-LM model has achieved the best results when it is compared to other ANNs models (newrb and GAs-MLPNNs). According to the results, it has been found that MLPNNs using the Levenberg-Marquardt algorithm revealed a great number of water losses and water demands with small Mean Square Error values. The results of the newrb model were highly precise as well, despite being less accurate compared to the MLPNNs-LM model. While the GAs-MLPNNs model could also generate predictions with a small Mean Square Error value, unfortunately, it was the least accurate model when it was put into comparison with the other models applied in this experiment. The ARIMA model was the least accurate in comparison to other NNs models because the ARIMA model relies on linear data to be accurate. This research is limited, so it was applied to one of the main cities in Palestine only, where the water data of demand and losses were collected monthly. In future work, we will work on the prediction model that existed in dynamic adaptive water systems to reduce the losses in the water network and will generalize the method to all data in all Palestine cities

REFERENCES:

[1] El Khateeb, M.E. and M.A. Salaime, Quality of Drinking Water from Rainwater Harvesting Cisterns of Hebron City and Factors Affecting It. 2009.

[2] Mimi, Z., et al., Evaluation of water losses in distribution networks: Ramallah as a case study. Water Science and Technology: Water Supply, 2004. 4(3): p. 183-195.

[3] Awad, Mohammed. "Forecasting of chaotic time series using RBF neural networks optimized by genetic algorithms." Int. Arab J. Inf. Technol. 14.6 (2017): 826-834.

[4] KHANDELWAL, Ina; ADHIKARI, Ratnadip; VERMA, Ghanshyam. Time series forecasting using hybrid ARIMA and ANN models based on DWT decomposition. Procedia Computer Science, 2 15, 48: 173-179.

[5] Awad, Mohammed, and Mohammed Zaid-Alkelani. "Prediction of water demand using artificial neural networks models and statistical model." International Journal of Intelligent Systems and Applications 11.9 (2019): 40.

[6] KOFINAS, D., et al. Urban water demand forecasting for the island of Skiathos. Procedia Engineering, 2014, 89: 1 23-1 3 .

[7] SAMPATHIRAO, Ajay Kumar, et al. Water demand forecasting for the optimal operation of large-scale drinking water networks: The Barcelona Case Study. IFAC Proceedings volumes, 2 14, 47.3: 1 457-1 462.

[8] HERRERA, Manuel, et al. Predictive models for forecasting hourly urban water demand. Journal of Hydrology, 2 1 , 387.1-2: 141-15 .

[9] Jang, D. and G. Choi, Estimation of Non-Revenue Water Ratio for Sustainable Management Using Artificial Neural Network and Z-Score in Incheon, Republic of Korea. Sustainability, 2017. 9(11): p. 1933.

[10] Chang, M., and J. Liu. Water demand prediction model based on radial basis function neural network. in 2009 First International Conference on Information Science and Engineering. 2009. IEEE.

[11] Kutyłowska, M., Comparison of two types of artificial neural networks for predicting failure frequency of water conduits. Periodica Polytechnica Civil Engineering, 2017. 61(1): p. 1-6.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[12] Sebri, M., ANN versus SARIMA models in forecasting residential water consumption in Tunisia. Journal of Water Sanitation and Hygiene for Development, 2013. 3(3): p. 330-340.
[13] Ajbar, A. and E.M. Ali, Prediction of municipal water production in touristic Mecca City in Saudi Arabia using neural networks. Journal of King Saud University-Engineering Sciences, 2015. 27(1): p. 83-91.
[14] Jabari, S.J., Non-Revenue Water Management in Palestine. World Academy of Science, Engineering and Technology, International Journal of Civil, Environmental, Structural, Construction and Architectural Engineering, 2017. 11(7): p. 953-959.
[15] Mahmoud, K.O. and D.M.A. Shanab, Forecasting Monthly Water Production in Gaza City Using a Seasonal ARIMA Model. Scholars Journal of Physics, Mathematics and Statistics, 2014. 1(2): p. 61-70.
[16] Box, G.E., et al., Time series analysis: forecasting and control. 2015: John Wiley & Sons.
[17] Hipel, K.W. and A.I. McLeod, Time series modeling of water resources and environmental systems. Vol. 45. 1994: Elsevier.
[18] Hamdan, Ihab, Mohammed Awad, And Walid Sabbah. "Short-Term Forecasting of Weather Conditions in Palestine Using Artificial Neural Networks." Journal of Theoretical & Applied Information Technology 96.9 (2018).
[19] Qteat, Haneen, and Mohammed Awad. "Using Hybrid Model of Particle Swarm Optimization and Multi-Layer Perceptron Neural Networks for Classification of Diabete." Int. J. Intell. Eng. Syst 14 (2021): 11-22.
[20] Amro, Hamsa, and Awad, Mohammed. "Prediction of Body Fat Percentage Based on Anthropometric Measurements Using Data Mining Approach." Journal of the Arab American University 7.2 (2021): 1-21.
[21] García-Pedrajas, N., C. Hervás-Martínez, and J. Muñoz-Pérez, COVNET: a cooperative coevolutionary model for evolving artificial neural networks. IEEE Transactions on neural networks, 2003. 14(3): p. 575-596.
[22] Dwaikat, Mohammed I., And Mohammed Awad. "Hybrid Model for Coronary Artery Disease Classification Based on Neural Networks and Evolutionary Algorithms." Journal of Information Science and Engineering 38.5 (2022): 1001-1020.
[23] Okasha, M.K. and A.A. Yaseen. Comparison between ARIMA models and artificial neural networks in forecasting Al-Quds indices of Palestine stock exchange market. in The 25th Annual International Conference on Statistics and Modeling in Human and Social Sciences, Department of Statistics, Faculty of Economics and Political Science, Cairo University, Cairo. 2013.
[24] Wan, E.A., Neural network classification: A Bayesian interpretation. IEEE Transactions on Neural Networks, 1990. 1(4): p. 303-305
[25] Bazartseren, B., G. Hildebrandt, and K.-P. Holz, Short-term water level prediction using neural networks and neuro-fuzzy approach. Neurocomputing, 2003. 55(3-4): p. 439-450.
[26] Riedmiller, M. and H. Braun. A direct adaptive method for faster backpropagation learning: The RPROP algorithm. In Neural Networks, 1993. IEEE International Conference on. 1993. IEEE.
[27] Hornik, K., M. Stinchcombe, and H. White, Multilayer feedforward networks are universal approximators. Neural networks, 1989. 2(5): p. 359-366.
[28] Lourakis, M.I., A brief description of the Levenberg-Marquardt algorithm implemented by levmar. Foundation of Research and Technology, 2005. 4(1): p. 1-6.
[29] Awad, Mohammed. "Optimizing the Topology and Learning Parameters of Hierarchical RBF Neural Networks Using Genetic Algorithms." International Journal of Applied Engineering Research 13.10 (2018): 8278-8285.
[30] Pomares, Héctor, et al. "An enhanced clustering function approximation technique for a radial basis function neural network." Mathematical and Computer Modelling 55.3-4 (2012): 286-302.
[31] Awad, Mohammed. "Enhanced hybrid method of divide-and-conquer and RBF neural networks for function approximation of complex problems." Turkish Journal of Electrical Engineering and Computer Sciences 25.2 (2017): 1095-1105.
[32] Awad, Mohammed. "Forecasting of chaotic time series using RBF neural networks optimized by genetic algorithms." Int. Arab J. Inf. Technol. 14.6 (2017): 826-834..
[33] Thornton, J., Water Loss Control Manual. 2002: McGraw-Hill.
[34] Ashour, Marwan. "Cash Flow Forecasting Using Probabilistic Neural Networks." Journal of the Arab American University 5.1 (2019): 1-14.