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Prediction of small hydropower plant power production in Himreen Lake dam (HLD) using artificial neural network

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Abstract In developing countries, the power production is properly less than the request of power or load, and sustaining a system stability of power production is a trouble quietly. Sometimes, there is a necessary development to the correct quantity of load demand to retain a system of power production steadily. Thus, Small Hydropower Plant (SHP) includes a Kaplan turbine was verified to explore its applicability. This paper concentrates on applying on Artificial Neural Networks (ANNs) by approaching of Feed-Forward, Back-Propagation to make performance predictions of the hydropower plant at the Himreen lake dam-Diyala in terms of net turbine head, flow rate of water and power production that data gathered during a research over a 10 year period. The model studies the uncertainties of inputs and output operation and there's a designing to network structure and then trained by means of the entire of 3570 experimental and observed data. Furthermore, ANN offers an analyzing and diagnosing instrument effectively to model performance of the nonlinear plant. The study suggests that the ANN may predict the performance of the plant with a correlation coefficient (R) between the variables of predicted and observed output that would be higher than 0.96.

1. Introduction

Hydropower golden age was in the first half of the 20th century before oil control on the force of dominant in the provision of energy. Several growth republics gradually began to get rid of traditional energy origins that built on oil, coal, and natural gas, owing to oil price increment, fossil fuel cost, thermal pollution and crisis of worldwide energy and renewable hydro plants facilitated over conventional [1].

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Currently, the power demand is growing with all day, which need more generation resources and different grid constructions. The developing countries that need to get and make enough resources must achieve load cracking so as to accomplish stability of the power system. While the load is increasing, the generators that coupled to a hydro-turbine begin to be sluggish affected on changing the output by reducing the frequency of electrical power. Thus the entire system would collapse; this situation is called blackout or cascaded failure [2]. Usually, reliability observations of generation systems regard the resource of energy for the power production as available continuously. This indicates that just one cause of the power production deficit has been an electrical generation part fiasco of power plant generally. In the hydropower production situation, when the reservoir is sufficient to assure the energy, abundance of power production is over the rule of the flow rate of water so that this model is right [3].

The flow rate of water in discharge gates is a suitable choice for the optimization difficult and it relies on the relevance among the capacity of the hydro-turbine in the reservoir and the water height in the reservoir (hydro-turbine net head). The hydropower production structure is regarded as essential basics for the accurate modeling of the optimization difficult in Small Hydropower Plants (SHP). The structure links up in the hydropower system let plans on how the water can smoothly be achieved in all detail of discharges of the hydroplant. In power production optimization of hydro-turbine, the relation between the flow rate of water and power production regarded as complicated and nonlinear; rely on the unit numbers in operation. It has been gotten more complicated because the system general loss relies on the all units discharged in the plant. The behavior and situation of nonlinearity method rely on linear programming success, where one of the production path solutions is a mixed integer with linear programming model [4].

In fact, the main reason of high reliability on the work of the Himreen lake dam Hydropower plant was on the dam not on the river. In spite of the high reliability of actual power production in this hydropower plant, it is unstable due to change in load demand and flow rate of water inputs to the turbine.

The method in this paper represents the dam flow rate and net head as variables to hydro turbine inputs and the power Production of generator unit was variables of output by using artificial neural network model. Experimental data (net head, flow rate and power production) for specific locations in Himreen lake dam hydropower plant were used as variable input-output parameters. Experimental mathematical analysis has been performed dependable inputs and output values of Hydropower plant.

The problem is how to overcome the complicated relations that happen between a variety of operations and identify the dynamic performance of Himreen Lake dam Hydropower plant by applying an ANN model. Operation and control of the specific plant can be succeeded by emerging an ANN model for making the plant performance prediction relying on previous observations certain data to product excellence parameters. Moreover, analysis of hydropower production is difficult quietly because of the complex existence of nonlinear relationships in the input variable. Power analyses present an essential part of the plan and process in several works of riverine resources planning and development.

The target of this work is to discover the artificial neural network's ability to predict power generation regarded as the main role in the training the networks and to establish relationships among input-output hydropower plant through a feed forward with back propagation algorithm. Moreover, the main purpose was to overcome high nonlinear of the specific system by applying the method of soft computing. Thus, numerous ANN models have been developed properly and typical parameters are employed to predict the models' accuracy. Owing to the prediction of higher accuracy, among many Artificial Intelligence (AI) built on soft computing methods, the artificial neural network (ANN) is used widely in specific operations. Therefore, the Artificial Neural Network (ANN) gives a fast and flexible passage for integration of data and development of the model.

2. Small hydropower plants (SHP)

The hydro-turbine obtains mechanic hydropower and changes it to rotational power mechanically and it's coupled to an electric power generator. Actually, the turbine efficiency depends on the turbine's power, the turbine's type, fluid percentage, etc. Kaplan turbine may be observed that its efficiency is reaching to the maximum value for a various flow rate of water, proving these kinds of turbines can be desirable for a river with a variant in the regime of water flow rate [3]. The unit of generating power of a hydropower plant relies on four factors which are ground acceleration, the flow rate of water, the height of the water drop and the general efficiency, which illustrated in Eq. (1)

$$P = \eta \cdot Q \cdot H \cdot g \tag{1}$$

P = generated power (KW);
g = ground acceleration;
Q = flow water rate (m^3/s);
H = net head of Turbine (m);
η = general efficiency

In general, the electrical power generators employed in Small Hydropower Plant (SHP) are synchronous machines which generate electrical power by alternating current, where, this synchronous machine has been strongly linked up with the turbine shaft to convert the mechanical rotational energy into electrical power [2,5].

3. Development of artificial neural networks

ANNs are a computing model derived from the brain of the human being and system of nervous. ANNs can essentially simulate regular intelligence since they study skills and make superior to other models. Moreover, they are "data-driven" and contain several numbers of interconnected operation elements known as neurons [6,7]. They also contain an input layer, hidden layer, and output layer respectively. They have the ability to learn, save and make relevance between inputs and outputs, which have the capability to be missed from experiential procedures [8,9].

The learning operation of ANNs happens by regulating the weights related to all correlations, and for this reason, the real output is corresponding to the wanted output. ANNs are essentially a statistical instrument and regarded as a kind of nonparametric regression model. ANN has been employed to make a solution to complicated difficulties in lifetime conditions by creating a prediction and classification so that they have been become a real part of models of prediction to apply uncertainty situations [10–12]. Because the instrumentation and measuring are expensive, there are some of necessary needs to discover another method that makes measuring or prediction accurately. ANN is an active option since it has an accuracy of prediction sufficiently when making a comparison to classical methods [13].

3.1. Identification and properties of ANN models

The majority of ANN models consist of three layers, and the architecture of these models are input, hidden and output layers as illustrated in Fig. 1. Each layer is additionally formed neurons of the artificial network named as nodes. Allover well-known parameters' information is regarded as an input to the input nodes. In return, these input nodes send forward this information to all over hidden layer nodes. Hidden nodes received the information through overall input nodes and then the node of bias in the input layer is gathered as illustrated in Eq. (2);

$$x_H = \sum_{j=1}^{j=n} w_{hj} i_j + w_{hb} b_{i,} \tag{2}$$

where X_H is the gathered input, W_{hj} is the general weight between input and hidden layer, W_{hb} is the general weight between hidden and bias node of the input layer, 'b' is the bias node of the input layer, and 'i' is the input node. Then, mathematically X_H is preceded by using the activation function. There are some of the different types of activation functions have been employed by several researchers [14,15].

3.2. Network types

The purpose is providing a valuable type model related to solving a problem and proving information engineering. The prime structure of ANN is learning adjustment, generality, parallelization, stiffness, association stored information and processing information. Thus the more commonly network employed in ANNs is the Multi-Layer Perceptron (MLP), The Single-Layer Perceptron (SLP), and Feed-Forward based on Back-Propagation (FF-BP) algorithm. The Single-Layer Perceptron (SLP) of the network contains the inputs, hidden and output layers correlated by biases and weights. The neuron numbers in the hidden layer of SLP are settled from three up to twenty-five [16–19].

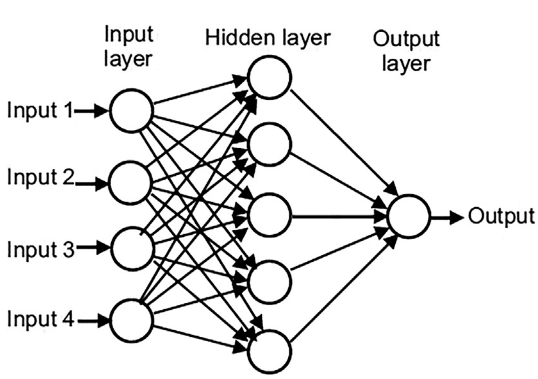

Figure 1 Structure of the ANNs.

3.3. The network activation function

The method of mean square error (MSE) is most commonly used for indication of predicting errors in overall training vectors. It's very valuable to make comparison among different models and it also illustrates the ability of the network to predict the accurate output. The MSE can be presented as in Eq. (3).

$$MSE = \frac{1}{n}\sum_{i}^{n}(h_i - h_m)^2 \tag{3}$$

where h_i and h_m are the real and forecasted output values respectively, for all the ith training vectors and N is the entire values of training [20]. The Root Mean Square of Error (RMSE) was employed to measure a performance of the network training by using Eq. (4), where h_n illustrates the measured value of output and number of training patterns is illustrated by n [21,22].

$$RMSE\ (\%) = \sqrt{\frac{\left(\sum_1^n (h_n - h_m)\right)}{(n-1)}} \tag{4}$$

Mean Absolute Error (MAE) was employed to make filtering in the most likely optimal networks on two cases training and checking data sets. Training and checking of the network performances are resolved by taking the considered outcomes of the mean absolute error (MAE) as presented in Eq. (5). Obviously, the typical values of RMSE and MAE are zero or nearly zero [23,24].

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|h_n - h_m| \tag{5}$$

The correlation coefficient (R^2) is widely used to check the predictions of output accuracy level. It was computed to choice the best and right network by using Eq. (6) [25].

$$R^2 = 1 - \sqrt{\frac{\left(\sum_1^n |(h_n - h_m)|^2\right)}{h_n}} \tag{6}$$

3.4. Standardizing and normalized data

The neuron numbers in all input-output layers have been selected corresponding to the designated influences and operation responses completely. The input and hidden layers have been specified a sigmoidal transfer function that was commonly employed to relationships of complex and nonlinear [26,27]:

$$f(x_U) = \frac{1}{1 + e^{-x_U}} \tag{7}$$

where X_U is the weighted algebraic summation of inputs into the transfer function and where the hidden layer working is computing the outputs through the inputs and forwarding all to the output layer as inputs automatically. Eq. (7) was approved to be the logarithmic Sigmoid function is the most commonly used for neuron activation function and is created for the slope and construction activation of ANNs. Thus, this makes equilibrium between linear and nonlinear performance. The output variable of the logarithmic sigmoid function is limited from 0 to 1, which is regularly selected by using the signal whose output variety range is between 0 and 1 [28,29].

All vectors in Eq. (8) are normalized function employed to obtain the feature standards of values between the ranges from 0 to 1 before fusion individuality by using all min values and all max values in normalization method given as follows:

$$X_i = \frac{X_{ni} - \min(X_n)}{\max(X_n) - \min(X_n)} \tag{8}$$

where, $X_n = (X_{n1}, \ldots, X_{nn})$ and X_i is ith normalized data. X_{ni} is the ith input data that need to normalize it. Eq. (8) is used as the mathematical formula is described and employed in the MATLAB codes were built into the data normalized. Thus, all inputs-outputs data values have been scaled into the range of 0–1. The neural network's prediction was tested by the outcomes and then made comparing with the real standard analysis data set for the selected duration. Ordinarily, the range of normalized amplitude in the neuron output is limited either as the interval of near item (0–1) or as the optional (−1 to 1). The logistic function sufficiently accepts a continual variety of values between (0 and 1), and it's simply distinguished [30,31].

4. Climate scenarios and flow rate variation in hydropower production

It should be highlighted that the influence of temperature and rainfall on the flow of water rate for the same month and the previous ones. In fact reason for this temperature and rainfall from the previous period might influence the flow of water rate in the next period and it would be high because of climatic condition influence during a previous period [32].

The investigated flow scenarios were employed to build on the operational constraints of winter hydropower. During considered period of 1985–2010 hydropower plants stopped 36 times, in which 29 times were shut down between 1 and 2 h, the longest noticed shutdown was 6 h. By using mentioned information, the scenarios were investigated built on a set of shutdown periods of a hydropower plant and the obligatory shutdown of the upstream hydropower plants.

The related influences the stability of the ice cover in the reaches downstream and the ice and environmental situations in the upstream reaches of a hydropower plant. The reason for matter of several shutdowns is that there are limitations on water upstream during the period of shutdown given to stop an ice breakup in the reaches downstream and following flood problems downstream in the regulation permit [4,33].

5. Study case and area

Province of Diyala/Iraq has been frequently exposed to several major floods along the Diyala River. There are five times of major floods occurred between the years of 1946–1986. Such floods usually lead to the human life loss and huge scale damage to the agricultural region and properties in the vicinity of the rivers. Thus the main purpose of this dam was to put flood under control, irrigation and hydropower production.

The study area was located in Himreen town as illustrated in Fig. 2. This area is located in the Province of Diyala/Iraq. The Himreen Dam is a dam at the end of the Himreen mountain range that contains Himreen Lake and it is about 100 km northeast of Baghdad, Iraq. It is employed to control the water flow of the Diyala River and its specifications are as follows: Dam Length: 3360 m, maximum height: 40 m, the amount of dictation: 3.65 million cubic meters of dirt, mud, consisting of pulp deaf and there to fill the origin of a concrete quantity: 150,000 cubic meters of liquefied water.

Structurally, this dam was built between the years of 1986 to 1991 by the Yugoslav company GIK Hidrogradnja (of Sarajevo, now Bosnia-Herzegovina). All the equipments of the Himreen hydropower plant such as gates, turbines, generators were also fully completed by the -Yugoslav companies. This plant consists of two units with a total installed capacity of 50 MW. Its turbine type used is Kaplan; K5S-3.8/3.686 and the generator type used is three phase synchronous with permanent magnet

6. Data set collection and train model

Artificial Neural Networks (ANNs) model was used to develop model simulations of Himreen Lake dam hydropower Plant. This small hydropower plant is located in Diyala/Iraq that serves to produce electrical power for feeding power to the people beside it.

Measurements of the parameters that include net head, flow rate, and power production have been collected over a 10 year period, and the obtained data were from 1st January of 2005 to 31th December of 2015. This duration was properly acceptable and it includes all seasons, which cover all the different possibilities in the work variables because all over the historical data are taken out on a daily reading basis. These historical data have brought and been checked from two ministries (The two ministries of water resources and electricity in Iraq) since the dams and hydropower plants are a related field between these ministries. Thus the data used are reliable due to checked from two specific destinations.

All data are used carefully and there is no delete and negligible for any raw data except little days indicated for cut-off power transmission lines that are not exceeded to one month collectively and its data not taken into consideration are not noted. The chosen dam covered the ranges of stable irrigation channels and drains with flow rates of water from 8 m^3/s to 175 m^3/s as shown in Fig. 3. Net head of turbine from 14.17 to 29.84 meters is shown in Fig. 4 and power production from 0 to 44,000 KW is shown in Fig. 5. On the other hand the value of zero generation was due to a very few maintenance workers that are less mature in the power production safety and they leave the turbine works as a default with no power production and water flow through it at very few periods.

The weather in all over Iraq may be considered as warm nicely, and it's more than 45 Celsius of a summer season. In return, the winter season turns into the cold with the regular temperature and that goes down to the end of 5 Celsius. But there is no time period of snow and frost as shown in Fig. 6. Thus, there is no shutdown of Himreen Hydropower plant and it can work continuously for all year times.

Production data of small hydropower plant (SHP) actually have a complicated and nonlinear relation, and may be contained irregular and loud data. And the measurement of the variable data is commonly changed that creates values of unre-

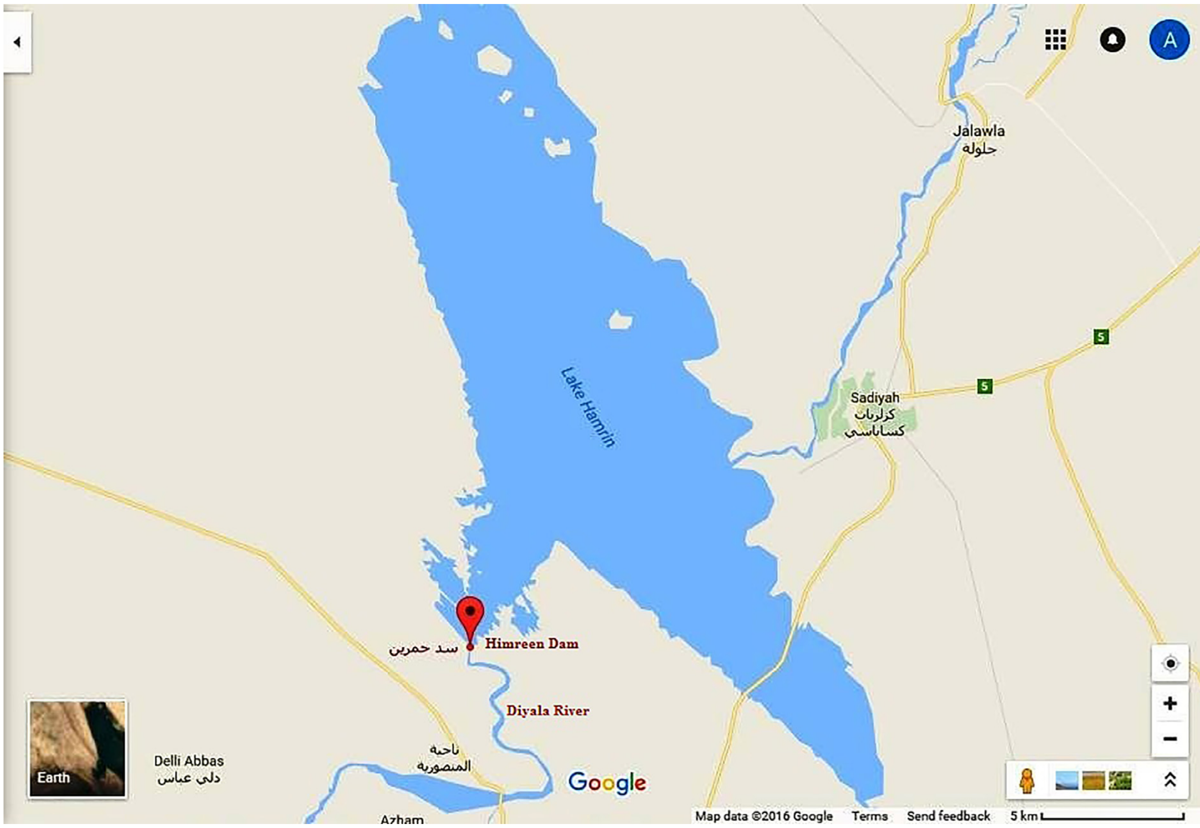

Figure 2 Himreen Lake dam.

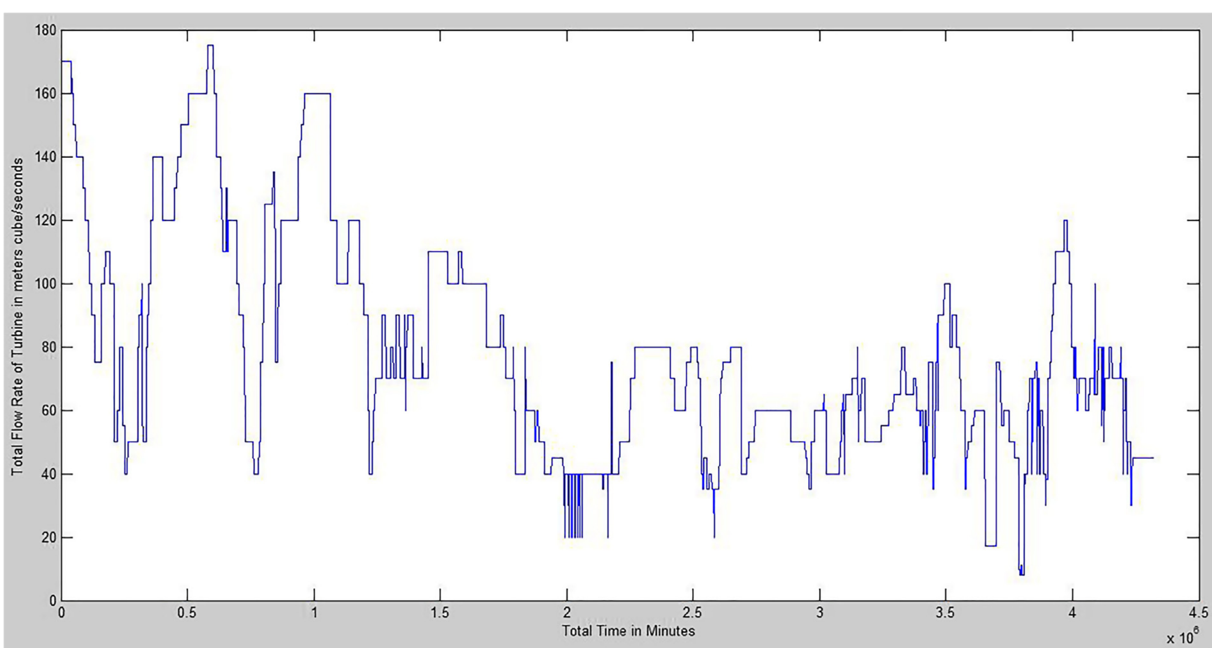

Figure 3 Chronological flow rate of water.

lated variables. In this work, the parameter inputs are classified into variable data and fixed data according to the inputs-output of the power rule in Eq. (1), which are net head of the turbine (in meter) and flow rate of the water (in m^3/s) as regards variable inputs, efficiency (in percentage) and ground acceleration (fixed value = 9.81) which are regarded as fixed inputs. The output variable data represent the actual power generation (in KW), where the number of data on inputs–out-

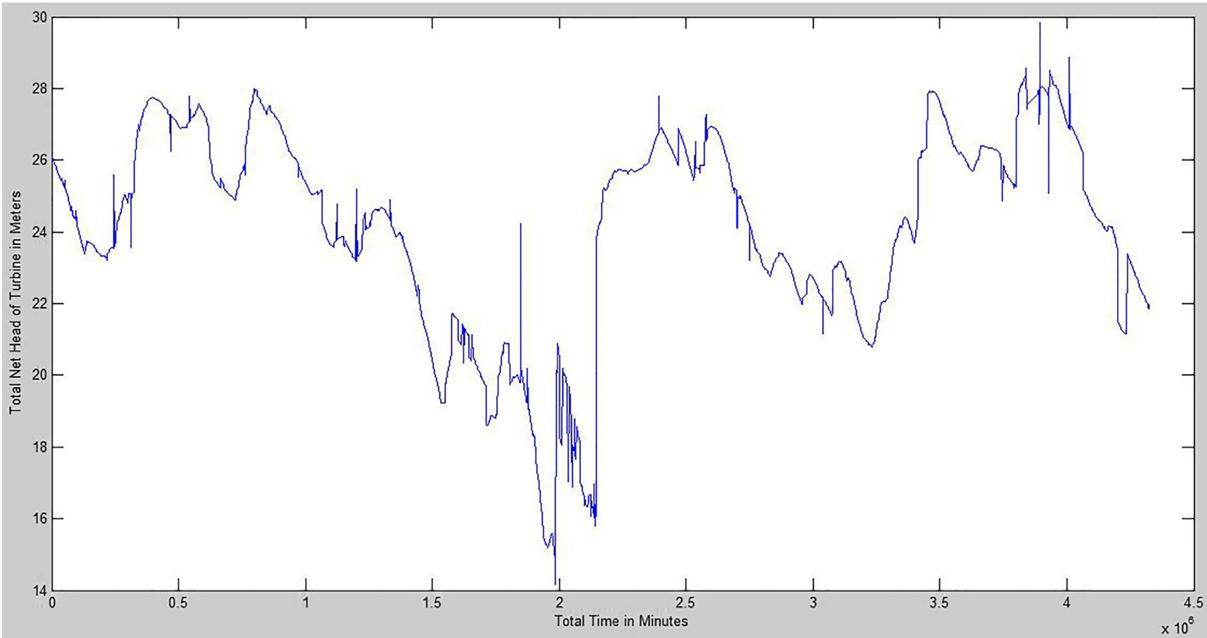

Figure 4 Chronological net head of turbine.

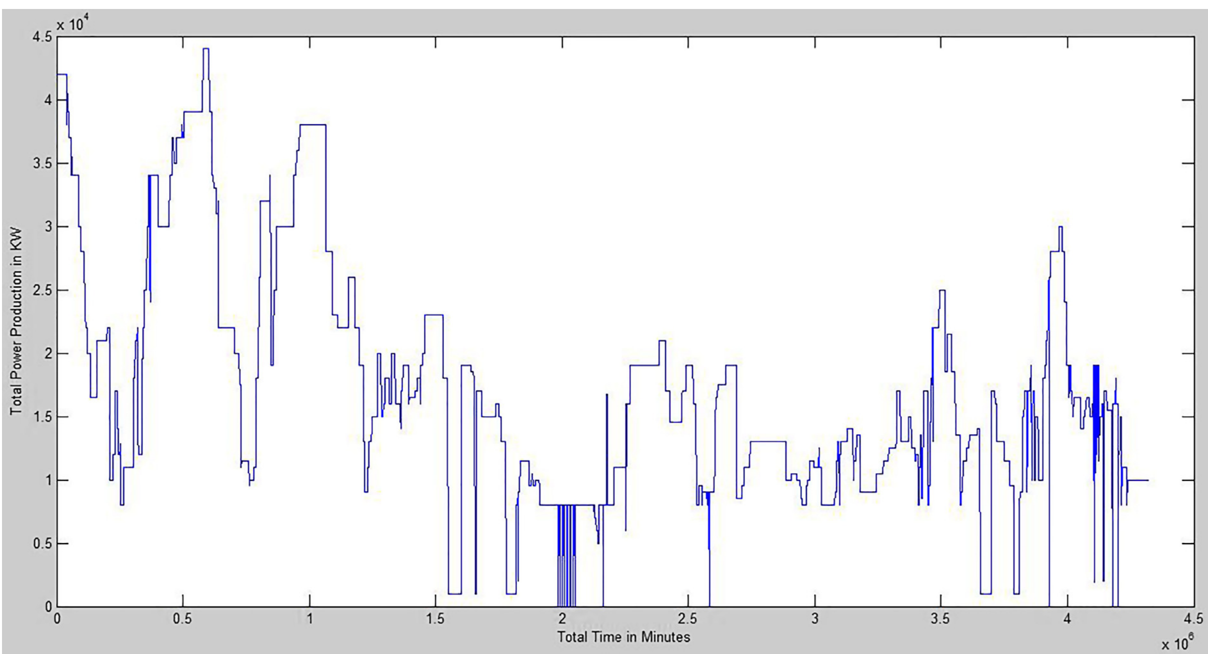

Figure 5 Chronological power productions.

put used are 3570 rows in MS-Excel. And then the preprocessed data set was analyzed statistically and classified into five columns in a matrix chronologically. Finally, the modeling and the matrix are arranged on variables of power rule in Eq. (1).

As shown in Eq. (8) all input and output data were scaled between (0 and 1) because it is easy to work and get fine results of normalized data, where X function is employed for all inputs-outputs data used in this study. Eq. (8) is used as the mathematical formula described and employed in the MATLAB codes that were built into the data normalized. Thus, all data used has normalized then using in ANNs to train.

After implementing the statistical analysis stage, the model of the neural network was simply generated by using MATLAB software that deals with applying simulation. When offered data patterns, historically measured input-output data sets relating the difficulties to be modeled, ANNs have the ability to create mapping and build up relation model for input and output data. This intended map was between relations of input and output in the ANN model construction, let's

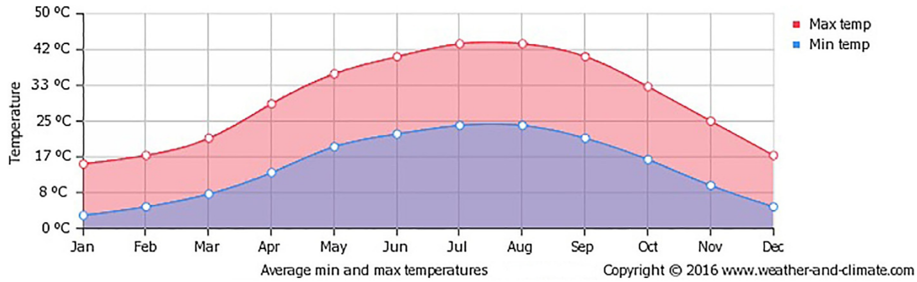

Figure 6 Average min and max climate temperatures at work site.

make a prediction for the value of the model output parameter in suitable accuracy for every possible assembly for a model of the input given data. However, the success of an ANN application relies on both the quantity and the quality of available data.

In this study, there were some of the networks used to train and predict power production using a software Matlab package of the R2015a version (The Mathworks Inc.) which is employed to apply ANN. To train the selection of prediction models, the learning algorithm such as Levenberg–Marquardt was specialized in the training. Among all diverse artificial intelligence built in soft computed methods, the artificial neural networks (ANNs) have been engaged widely in machining actions due to the high accuracy of the process performance prediction. Actually, there are some of the diverse network types; the most widely employed network types of Feed Forward Neural Networks (FFNNs) are known as Back Propagation (BP) that is employed in this study. Since creating an ANN model depends on the historical data, therefore the input and output data grouped during this study were analyzed statistically. ANNs were specialized built on 4 inputs and 1 output. Certainly, there are some of the main variables which may be employed to evaluate the plant behavior.

MATLAB Toolbox is opening the Data Manager window of Neural Network that lets the user import, create, and then export neural networks and data are created. Nevertheless, Neural Network Training window illustrated the Network characters as follows:

- Network inputs: Net Head, Flow Rate of Water, Efficiency and Ground Acceleration.
- Network target: Power Production.
- Network type: Feed-Forward Back-Propagation.
- Function of training: TRAINLM.
- Adjustment learning function: LEARNGDM.
- Function of performance: MSE.
- Hidden layer numbers: 1.

Previously and up to now, there is no rule for selecting the neuron numbers or the middle layer numbers in the network. The correct way is built on trial and error. Therefore, there are some of the diverse neuron numbers and internal layers are tried and assessed. The execution of each model is checked, and the structure with the minimum number of neurons and internal layers is usually selected as illustrated in Fig. 7.

The network has been trained using certain parameter sets. Allover inputs and output data were exploited for training this network. Fig. 8 illustrates diverse combination characters of the ANN which are verified to make training the network till the maximum regression coefficient (R) was accomplished. Thus, it's employed to regulate the behavior of the network training. Afterward several tests and executes with diverse of hidden layer numbers and the neuron numbers in every layer of the ANN, and they were selected to build on the maximum regression coefficient (R) of the ANN in each layer. A back propagation algorithm has been employed since this algorithm probability to calculate the inclination of every layer is applying condition principle iteratively.

X_i function in Eq. (8) is normalized and also employed a different gradation input and output layers. The different gradation has been served to train model of ANN by closing back-propagation algorithm. Then $F(X_U)$ function in Eq. (7) is employed to tangent sigmoid and straight linear functions that have been also employed in the transfer functions in the ANN hidden and output layers respectively. The Mean Square Error (MSE) among the actual outputs and output of neuron outcomes is computed and propagated backward through the network. Then this algorithm regulates the weight of everyone. On the other hand Figs. 9 and 10 illustrate the Mean Square Error (MSE), the value of best validation performance is 0.0032734, and its gradient of epochs is 0.00013636 respectively. Thus the training was all over and corresponds to ANN that was extremely constructed.

7. Result, discussion, and validation

By default, the artificial neural network employs the Levenberg–Marquardt algorithm for training. The serial employment endures to input vectors and target vectors established as continued: training; validating that the network is extrapolating and stopping trains already at over-fitting; and at ending the independent trial of network generality totally.

Fig. 7 illustrates a caption window of the neural network throughout the training. It also displays training developments and lets the user interrupt training at any point by using stop training button. Fig. 8 illustrates the results that come from the click on the regression switch in the training window. It achieves a linear regression among the matching targets and the network actual outputs.

When an ANNs model may peculiarly provide the maximum standards of the Correlation coefficient (R^2) and minimum standards of Root Mean Square of Error (RMSE) or Mean Absolute Error (MAE), it can be definitely approved to be the right and superior ANN model.

It is noticed from Fig. 8 that the output paths are targeted extremely for training (R-value = 0.9679), validation (R-

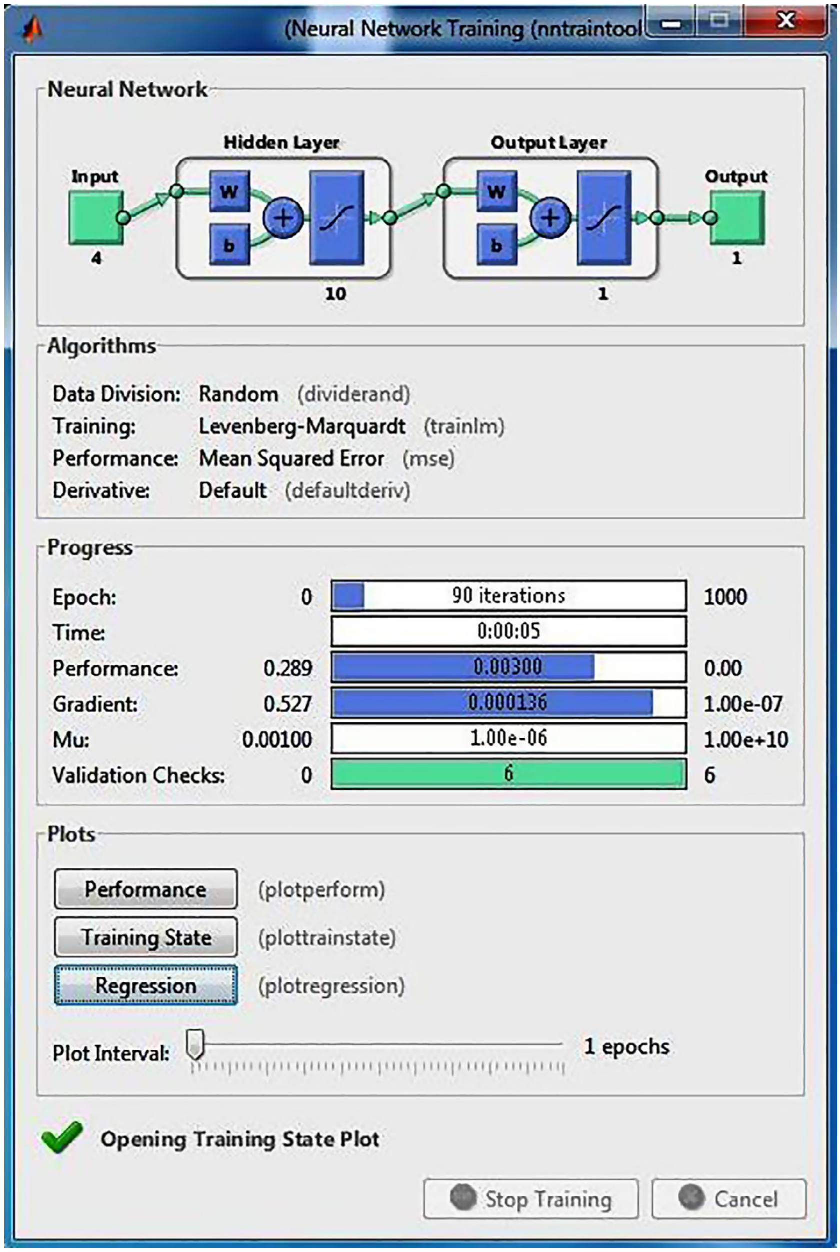

Figure 7 Training window of ANN.

value = 0.96294), and testing (R-value = 0.96251). These values could be corresponding to a total response of R-value = 0.96651. In this case, the response of the network is favorable so far, and simulation can be used for entering new inputs. The Regression (R) plot displays the relevance between the target that regards as the desired output and the ANN output that regard as an actual output. R = 0.9665 represents that ANN output extremely matches with the target. The Regression (R) value is obviously indicated the relevance between the outputs and targets. In general, when R is approaching 1, this means a precise linear relevance between targets and outputs. On the contrary, when R is approaching zero, this means a slight linear relevance between targets and outputs. In this study, the training data show a dependable propriety. Also the validation and checked outcome display values of (R) that are larger than 0.96.

The creation of ANN of the original data set is shown in Figs. 3–5 respectively, for net head and flow water rate as variable inputs and the actual power production as an output. Figs. 9 and 10 illustrate training variations of MSE, testing and validation data collection groups opposite to epoch throughout of the network training that displays the best validation performance at epoch 84–90. This indicates the effluent of net head and flow rate measures the results of predicted power output variables.

Moreover, this section compares the results of this study with the results from other major studies of production and forecasting using the artificial neural network. Direct comparisons are made with three modern research papers in this study such as Tahir et al. [2], Chiteka and Enweremadu [13] and Zhang et al. [27] and more general comparisons with Nasr et al. [12], Ghumman et al. [14].

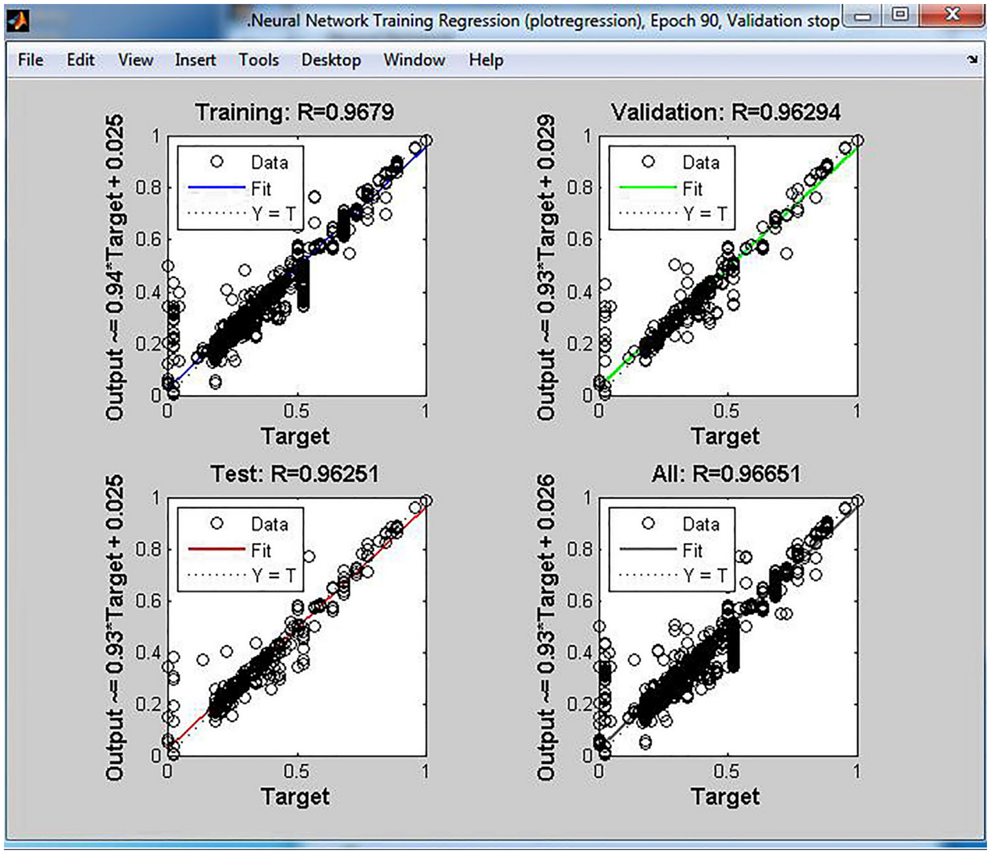

Figure 8 Regression plot of ANN.

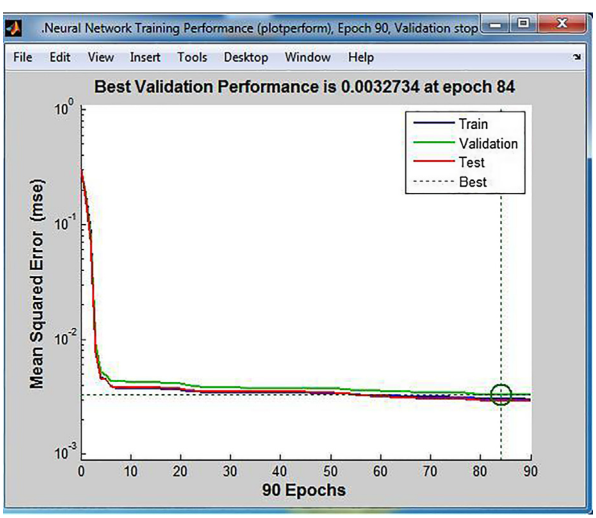

Figure 9 Training, testing and validation of MSE.

When considered clearly at the finest level of detail, there were some of the differences in the data set and methodology from study to another one relatively and it is really true when comparing this study with comparison studies. Regression (*R*) for comparison studies is 0.87, 0.90, 0.96, 0.90 and 88.95 respectively.

The reasons for the difference in comparison studies over the years reflect numerous kinds of major changes. First, numbers of collection data set are used in ANN train. Secondly, valid differences of view occur over analytic methods and approaches, How to reach the destination represented in number of 1 as the result of *R*.

8. Conclusion

The important conclusion is the availability of power generation of Small Hydropower Plant (SHP), and it is essential to model the availability of power energy related to the flow rate of water variation related to the generator unit. For the accurate modeling of the SHP availability, it was obliged to identify some particulars of the hydropower plant such as turbines' and generators' characteristic, the net head of the turbine and the flow rate of water more than a long-term duration of time.

In this work a successful execution of prediction of power production by using artificial neural networks (ANNs) including single-layer perception (SLP) with feed forward with back propagation algorithm has been accomplished. The analysis of the daily data set depended on the influences on the net turbine head and flow rate of water as an inputs and power produced as output. Particularly it was modeled using the actual observed daily data for the period 2005–2015. If the algorithm was applied to the similar data, the outcomes exactly enhanced which prove the used algorithm's excellence. Accurately ANN has been achieved the given training data so that it has noticed the system exact increment and also the generality capacity enhancement. The algorithm was employed, which made prediction didn't endure to the difficulties of the recent data set.

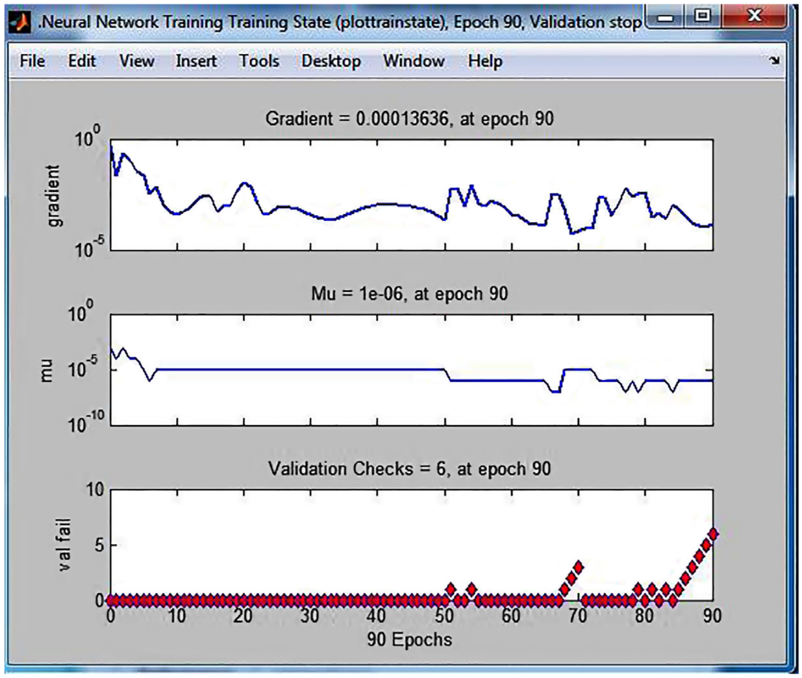

Figure 10 Gradient Epochs of network performance.

Thus the results were indicated by a high value of correlation coefficient (R^2) between the variables of predicted and measured output getting up to 0.96 and Root Mean Square Value (RMSE) value of best validation performance is 0.0032734, and its gradient of epochs is 0.00013636 respectively. Hence, this development model has been satisfactory for accuracy and capability of generalization and is suitable for the prediction models. Finally, depending on the high-value accuracy of ANN in prediction, the neural network modeling might successfully simulate and predict the behavior of all small hydropower plants (SHP).

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