Modeling of Hydropower Plant Production using Artificial Neural Network

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Abstract—A new prediction modelling approach for hydropower generation in the presence of input random variables is investigated in this paper. Firstly, they decomposed the annual input variables like the net head of the turbine, and flow rate of water into a certain number of detail signals through artificial neural network (ANN) transform. ANN model used to predict the annual power generation. After the stationary simulation prediction model is obtained, the prediction results were superposed. Finally, simulation results have demonstrated the robustness and effectiveness of this new approach when compared with the existing one.

Index Terms—Small Hydropower Plant; Artificial Neural Network; Prediction; Himreen Lake Dam

I. Introduction

For generating power, hydroelectric power is the most widely used renewable sources of energy. Hydro power generation depends on the available flow and altitude from which it falls [1, 2]. The main components of soft computing and Artificial Neural Networks (ANNs) [3]. Artificial Neural Network techniques can be used for modeling on the hydro generation scheduling extent at a certain point. These techniques are less subjected to the constraints of physical description and ability to map the logical input/output relations [2, 3]. the ANN model performs in some cases better than the physically-based models [4].

Several related works include two main techniques like ANN using different case studies in hydro power generation to forecast stream flows using hybrid wavelet-neuro-fuzzy model [5], modeling daily discharge [3]. Prediction using neuro-fuzzy approach for Short-term water level [2], and long term [6], and automatic generation control of multi-area power system [7]. Hybrid neuro-fuzzy approach for automatic generation control [8], modeling for three-phase [9], and predict speed [10, 11]. Rough artificial neural network using for classification [12-14], Modeling of ANFIS [15, 16], and prediction [17, 18].

From a modeling viewpoint, a Hydropower operation is a unpredictable [9], complex [3] due to the stochasticity of hydrologic variables [19], non-linear system [20] due to uncertainty of the process [1], non-minimum phase system [9, 20], uncomfortable for managers and operators because of the complicated optimization techniques used in the models [19]. In addition, modeling hydropower systems, based on a power generation approach, usually requires a large number of input data, which are not readily available [2, 3]. Therefore, other models such as ANN rule-based models have been suggested to overcome these limitations [19]. Since the development of hydropower prototypes is costly, it is better to model by ANN model [9].

An enhanced neural network for optimal control is proposed, a new algorithm to realize the feature selection, with the intention to use the rough set as a tool for structuring the artificial neural network (ANN) by automatically computing the proper modelling thresholds instead of choosing them. On the other hand, it is to determine spatial distributions of input parameter values. In return, make output parameter values of the intermediate stations. moreover, because of the numerous parameters of ANN and the proposed to solve the optimized parameters selection problem.

II. Methodology

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A. Hydropower function

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. 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 [21-24].

The electric power output of a hydro generating unit i can be described by means of Eq. (1), which is known as the hydropower function:

$$Pp_i = 10^{-3} \times Nh_i \times Fr_i \times \rho \times g \times \eta_i \tag{1}$$

where 10^{-3} is a constant used to convert W into KW. According to Ref. [25-27], g, depends on the plant location, i.e., its latitude and elevation relative to the sea level:

$$g = 9.7803 \times \left[1+0.0053\times\sin^2(\phi)\right] - 3 \times 10^{-6} \times lcr_i \tag{2}$$

The water density, ρ, is a function of the water temperature, Te, and the elevation relative to the sea level. This parameter is calculated, according to Ref. [25-27], as follows:

$$\rho = \frac{100}{\sum_{z=0}^{3}\sum_{w=0}^{3} R_{zw} \times (Te-\theta)^{w} \times \left[10^{-5}\left[\rho_0\left(1-msm_i \times lcr_i\right)+2\times10^{7}\right]\right]^{z-1}} \tag{3}$$

$$Nh_i = Rfl - Rtl - \left[K_0\left(\frac{q_i}{Q}\right)\times Q^2\right] - \left[K_i^{ag} \times q_i^2\right] - hll^{atm} \tag{4}$$

$$hll^{atm} = \frac{\rho_0}{\rho \times g}\left[\left(1-msm_i \times Rfl\right)^{5.225} - \left(1-msm_i \times Rtl\right)^{5.225}\right] \tag{5}$$

For real-time operation, the turbine hydraulic efficiency, η_i, may be determined by means of two methods, which are also detailed later. Finally, related to the hydropower function (1),

$$\eta_i = \frac{output}{input} \tag{6}$$

$accoding$ to Eq.(1),(10); thus

$$\eta_i^{min} = \frac{Pp_i^{min}}{Nh_i^{min} \times Fr_i^{min} \times g} \tag{7}$$

$$\eta_i^{max} = \frac{Pp_i^{max}}{Nh_i^{max} \times Fr_i^{max} \times g} \tag{8}$$

The turbine losses, tl_i, and the generator losses, gl_i, must be defined. The , tl_i, are obtained by field tests and may be divided into three parts: losses due to mechanical friction in the guide bearings, losses due to shaft seals, and losses due to the thrust bearing. The first one is modeled as a function of gop_i. The portion due to shaft seals is assumed constant. The losses due to the thrust bearing, bl_i, are obtained in field tests, in which a curve relating the losses with , gop_i, is obtained. The , tl_i, are divided into two parts, related to the turbine and the generator of unit i [2, 22, 28], according to equations below:

$$Dg_i = \frac{Wg_i}{Wg_i + Wt_i + Bt_i} \quad (9)$$

$$Dt_i = \frac{Wt_i + Bt_i}{Wg_i + Wt_i + Bt_i} \quad (10)$$

Considering Eqs. (9) and (10), the thrust bearing losses related to the generator, bl_i^g, and related to the turbine, bl_i^m, are defined as:

$$bl_i^g = Dg_i \times bl_i \quad (11)$$

$$bl_i^m = Dt_i \times bl_i \quad (12)$$

Considering Eq. (1), the turbine input power, tip_i, turbine output power, top_i, generator input power, gip_i, and generator output power, gop_i, are defined as:

$$tip_i = 10^{-3} \times Nh_i \times Fr_i \times \rho \times g \quad (13)$$

$$top_i = tip_i - tl_i \quad (14)$$

$$top_i = gip_i + tl_i \quad (15)$$

$$gop_i = gip_i - gl_i \quad (16)$$

B. Himreen Lake Dam (HLD) Hydropower Plant

1) Dataset collection

Himreen lake dam 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 upstream, downstream, net head, flow rate, and power production have been collected over a 12-year period, and the obtained data were from 1st January of 2005 to 31th December of 2016. 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. 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 unrelated variables [28, 29]. Main design parameters of the hydropower plant are included in Table 1.

2) Actual observed system operator (AOSO)

The AOSO has variable parameters of himreen lake dam (HLD) hydropower plant. Where there are some relations between them. In a direct relationship, as one variable increases, the other increases, or as one decreases the other decreases. On the other hand, the type of relationship whereby if there is a change in one variable, then there will likely be a corresponding change in the other. This is a special form of linear relationship that gives us a changing our equation of a line.

All variable parameters of hydropower plant can also be referred to as a positive relationship because this corresponding change in the other variable is typically in the same direction. Often, a special form of direct relationship called a directly proportional relationship where the variables are increasing or decreasing at the same rate. Figs.1 (a), and (b) shows the coordinates point on the curve of net head and flow rate vs. power production. The range of net head and flow rate vs. power production do indeed a linear relationship.

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Therefore, the increase of flow rate, Fr_i^h, and net head of turbine, Nh_i^h, directly effects on power production, it can prove that by taking any different two points and compare with them. Moreover, there is an obvious relationship and direct linear proportionality with a high slope which leads to a strong increase in power production in any small change in the flow rate of water and net head of turbine when other variables are fixed as illustrated in Eq. (17) and Eq. (18).

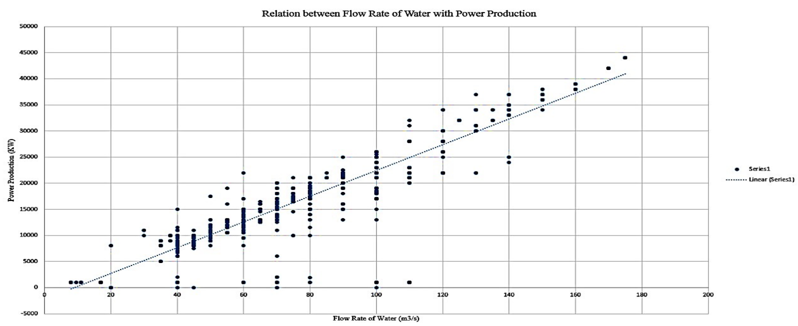

Figure 1(a). The relationship between flow rate of water and power production

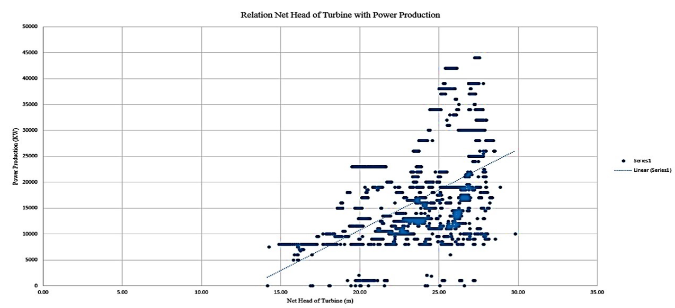

Figure 1(b). The relationship between net head of turbine and power production

$$Pp_i^h \propto slop\ Fr_i^h \tag{17}$$

$$Pp_i^h \propto slop\ Nh_i^h \tag{18}$$

3) Standard system operator (SSO) of HLD hydropower plant

The SSO built in the initial created values randomly which is corresponding to limitations of input variable parameters of hydropower system production. It's controlled by limitations which are according to standard system information. Whereas, Rand function is used for this purpose which generates a controlled random number in specific ranges. It's depending on the limitation of minimum and maximum allowed of the net head of turbine and minimum and maximum allowed of water flow rate as illustrated in Eq. (19) and Eq. (20) respectively.

$$Nh_i^s = Rand\ [Nh_i^{s,min}, Nh_i^{s,max}] \tag{19}$$

$$Fr_i^s = Rand\ [Fr_i^{s,min}, Fr_i^{s,max}] \tag{20}$$

4) Implementation the SSO by Matlab:

The flow rate of water, Fr_i^s, Includes 4015 rows and 1 is a column. 170 is a maximum range (stop point) and 8 is a shift range or it's a (start point). Rand function generates numbers between 0 and 1. So, the 178 is the maximum range and 8 is the minimum range. Total range period is 170 from 8 to 178 as illustrated in Eq. (21).

Moreover, net head of water, Nh_i^s, is also executed by rand function with a total range period is 30 from 14 to 16 as illustrated in Eq. (22). The SSO is more valuable due to it is created controlled random values with four decimal randomly depending on system standard information data [30].

$$Fr_i^s = Rand\ (4015,\ 1) * 170 + 8; \tag{21}$$

$$Nh_i^s = Rand\ (4015,\ 1) * 16 + 14; \tag{22}$$

5) Himreen lake dam (HLD) application

The gravity acceleration, g, depends on the plant location, ϕ, and the runner diameter of Kaplan turbine, lcr_i, HLD hydropower plant latitude runner and its turbine diameter will be 34.187999° and 9 m respectively. Thus, the gravity acceleration, g, = 9.7966 (m^2/s) as illustrated in Eq. (2). Standard air pressure or International standard atmosphere, ρ_0, for HLD is 101,325 Pa is between 0 °C to 100 °C as well as the Constant of Materials science and manufacture, msm_i, is 2.2558×10^{-5}. There is no shutdown of the Himreen Hydropower plant and it can work continuously for all year times due to water temperature range, Te_i^h, is from 0 °C to 55 °. Moreover, the maximum water density (ρ) is 999.97 which corresponds to water temperature, Te_i^h, that equal to 4 °C.

Table 1. Main design parameters of the hydropower plant [29, 31]

Hydropower plant parameter	**AOSO / SSO**
Maximum net head of turbine (m)	29.84 / 30.8
Minimum net head of turbine (m)	14.7/14
Maximum upstream (m)	101.8
Minimum upstream (m)	92
Maximum downstream (m)	75
Minimum downstream (m)	70
Number of turbine-generating units	2
Type of turbine-generating units	Kaplan-synchronous
Number of penstocks	2
Maximum Flow (m3/s)	174 / 178
Minimum Flow (m3/s)	8/8
Power (MW)	36.4
Maximum power(MW)	44 (2×25) / 50(2×25)
Minimum power(MW)	8/8
Maximum Reservoir volume (m^3)	3.95×10^9
Minimum Reservoir volume (m^3)	1.5×10^9
Maximum hydropower efficiency	94.1
Minimum hydropower efficiency	98.9

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C. Identification and Properties of ANN Models

The majority of ANN models consist of three layers, the architecture of these models are input, hidden and output layers. Each layer is additionally formed neurons of the artificial network named as nodes. Allover well-known parameters information regard 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 Eq. (23);

$$x_H = \sum_{j=1}^{j=n} w_{hj} i_j + w_{hb} b_i \quad (23)$$

where, X_H, is the gathered input, W_{hi}, 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, i, is the input node. Then, mathematically, X_H, is preceded by using the activation function. The more commonly network employed in ANNs is the Multi-Layer Perceptron (MLP), The Single-Layer Perceptron (SLP) algorithm.

The method of Root Mean Square Error (RMSE) 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 as presented in Eq. (24). Mean Bias Error (MBE) and Mean Absolute Error (MAE) were 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 both functions as presented in Eq. (25) and (26) respectively. The correlation coefficient (R^2) is widely used to check the predictions of output accuracy level. It was computed to choose the best and right network as presented in Eq. (27).

Where, h_i, and h_m, are the real and forecasted output values respectively, for all the, i^{th}, training vectors and, N, is the entire values of training [32-34].

$$RMSE = \sqrt{\frac{1}{N}\left(\sum_{i}^{N}\left(h_i - h_m\right)^2\right)} \quad (24)$$

$$MBE = \frac{1}{N}\left(\sum_{i=1}^{N}\left(h_i - h_m\right)\right) \quad (25)$$

$$MAE = \frac{1}{N}\left(\sum_{i=1}^{N}\left|h_i - h_m\right|\right) \quad (26)$$

$$R^2 = 1 - \sqrt{\frac{\left(\sum_{1}^{N}\left|\left(h_i - h_m\right)\right|^2\right)}{h_i}} \quad (27)$$

where, X_U, is the weighted algebraic summation of inputs into the transfer function? Where the hidden layer working is computing the outputs through the inputs and forwarding all to the output layer as inputs automatically. Eq. (28) was approved to be the logarithmic sigmoid function, which is the most commonly used for neurons activation function and a created for the slope and construction activation of ANNs. Thus, this makes equilibrium between linear and nonlinear performance [35, 36]. 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. All vectors in Eq. (29) are a normalized function that 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. On contrary, the de-normalized method can be used to get the original data values for all vectors that given in Eq. (30) [37, 38]:

$$f(x_U) = \frac{1}{1+e^{-x_U}} \tag{28}$$

$$x_{norm} = \frac{x-(x_{min})}{(x_{max})-(x_{min})} \tag{29}$$

$$x = x_{norm} \times \left((x_{max})-(x_{min})\right)+(x_{min}) \tag{30}$$

1) AOSO modeling elaboration using ANN

Because (i) a sufficient quantity of data has been acquired, (ii) the interaction between the inputs and the output of a Small Hydropower Plant (SHP) model (power curve) is non-linear, and (iii) analytical solutions to the impact of many parameters could not be found, ANN seemed to be a logical technique for modelling the power curve of a SHP. A feed forward neural network (also known as a multilayer perceptron (MLP)) with back propagation algorithm was therefore implemented. There is model (power curve) become more complex. For this reason, and because of the fact that interaction between independent variables has been depended on the power production rule in Eq. (1), modeling by means of successive steps single - stage modeling was developed. the power output is modeled according to Eq. (1) input variables with the net head, flow water rate, efficiency, and gravity acceleration.

2) Efficient modeling prediction

The ANN model was used to model the power production. The measured values of these inputs over the span of the experiment. The network was evaluated by comparing the network predicted outputs with the actual power production. To select the best model can be regarded the one that has lower functions of Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) which correspond to the template whose sequence provided overnights is closer to the actual power production, or can select the model with the highest regression (R) corresponding one whose sequence forecasts of power production follows best variations of the behavior of actual power production. Not always the model with the best MAE (lowest) present a better R (higher). The results of the derived SLP and MLP ANN models are shown in Table 2. According to Table 2, the best result in the ANN91 model. It has completely created by using trial and error method.

Table 2. Derived SLP and MLP ANNs

models	type	network topology	R^2 train	validation	test	all	RMSE	MBE	MAE
1	SLP	1*1	0.9531	0.92009	0.95822	0.94916	0.0680	0.0034	0.0372
4		4*1	0.95619	0.96648	0.9531	0.95698	0.0624	-0.0013	0.0315
7		7*1	0.9668	0.95118	0.96472	0.96414	0.0571	-0.0015	0.0287
10		10*1	0.95527	0.95676	0.95903	0.95515	0.0633	-0.0057	0.0310
12		12*1	0.96566	0.95471	0.963	0.9637	0.0574	2.5033e-04	0.0280
15		15*1	0.97197	0.97974	0.97169	0.97306	0.0496	5.2182e-04	0.0261
16		16*1	0.97093	0.96025	0.97301	0.96975	0.0525	7.2810e-04	0.0266
18		18*1	0.97654	0.96482	0.97847	0.97509	0.0477	-3.2266e-04	0.0235
21		21*1	0.96926	0.95142	0.95273	0.96433	0.0570	-0.0027	0.0289
23		23*1	0.97788	0.98249	0.96572	0.97681	0.0461	-2.0099e-04	0.0213
26		26*1	0.96809	0.94768	0.95358	0.96284	0.0581	-0.0014	0.0286
29		29*1	0.97264	0.98009	0.97706	0.97442	0.0483	3.5029e-04	0.0244
31		31*1	0.96914	0.9564	0.95263	0.96486	0.0565	-4.2715e-04	0.0288
37	MLP1	3*6*1	0.96327	0.9603	0.96654	0.96331	0.0578	0.0013	0.0281
39		3*8*1	0.95981	0.9599	0.94047	0.957	0.0624	-1.6794e-05	0.0304
43		3*12*1	0.95781	0.95204	0.95489	0.95651	0.0628	0.0011	0.0321
44		3*13*1	0.96739	0.9624	0.96736	0.96639	0.0549	-4.0349e-04	0.0251
49		3*18*1	0.96912	0.97369	0.96492	0.96903	0.0531	1.2227e-04	0.0285
52		3*21*1	0.96148	0.97216	0.96267	0.9578	0.0621	-0.0061	0.0309
55		3*24*1	0.97918	0.97276	0.95557	0.97473	0.0481	3.5804e-04	0.0225
58		3*27*1	0.95693	0.96702	0.95444	0.95822	0.0616	-5.9712e-06	0.0297

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61		3*30*1	0.97383	0.97932	0.98149	0.97576	0.0471	0.0011	0.0228
68	MLP2	5*7*1	0.95632	0.9704	0.96439	0.95961	0.0607	-0.0050	0.0295
70		5*9*1	0.96545	0.95463	0.96741	0.96407	0.0572	-7.6769e-04	0.0274
72		5*11*1	0.96639	0.96387	0.95604	0.96449	0.0568	-1.4128e-04	0.0264
75		5*14*1	0.96156	0.9697	0.95383	0.96145	0.0592	9.9457e-04	0.0298
78		5*17*1	0.95762	0.96331	0.96855	0.96029	0.0600	5.3349e-04	0.0299
83		5*22*1	0.96588	0.96775	0.94873	0.96363	0.0577	-0.0023	0.0274
86		5*25*1	0.97521	0.97032	0.97999	0.97504	0.0478	-7.4538e-04	0.0250
89		5*28*1	0.96521	0.96915	0.96663	0.96606	0.0556	-5.7994e-04	0.0262
91		**5*30*1**	**0.97941**	**0.97358**	**0.97771**	**0.97831**	**0.0446**	**-4.1496e-04**	**0.0204**

D. AOSO model simulation test

Neural network performance is dependent on the model building parameters such as training. In this particular application, the trained neural network demonstrated a generalized pattern learning capability by showing high correlations and low prediction errors between pairs of actual power production efficiencies and predicted neural outputs for both training and test data sets. The next stage of the experiment is aimed at exploring the nonlinear mapping capabilities of ANNs. For the implementation of neural network models, Matlab software was used by exploiting its built-in design capabilities. The backpropagation neural network (BPNN) model formed 5-30-1 network structures for structures model by generating the hidden neurons necessary for nonlinear pattern mapping.

To build the artificial neural network model, first, begin to build the matrix variables that were more correlated with the variable to predict and less with each other were selected and tested for the input layer. It was decided to include the input variables to have a significant correlation with the output variable and is highly correlated between them. At this stage of the work, the variables that will form the basis for construction of the models and will study the behavior for the reporting period. This article aims to model and predict the power production.

MATLAB R2015a software is used for modeling in this research and the process of preparation of information and their use in modeling. After, defining functions for ANN modeled used, like the number of layers and neurons in different layers and creating neural networks and training networks according to defined functions. At data manager window after finishing the creation of ANN, the export and save the network model is within reach. Then, call the save network model by Matlab instruction to display the created model and testing networks according to the defined data.

Once the converged solution of the first ANN has been obtained, defining the matrix data set to let them make a creation in workspace window. The input variables have been brought to the model window to use it for test and make it as inputs which are according to a variable of Eq. (1). On other hands, The ANN modeling for predicting the power production using the net head of turbine, the flow rate of water, efficiency, and ground acceleration as first, second, third and fourth inputs to model respectively. It is sequenced correspondingly to the input variables of ANN model created form first to fourth inputs to let every input enter to same its position in ANN model created according to network inputs sequenced as mentioned before.

Afterwards, Normalized for the average density of the experimental data. The activation function here to normalize the input data to modeling for test and was deployed the logistic function (sigmoid function) with a minimum and maximum value of 0 and 1, respectively. On other hands, it is used to convert ever values of every input between 0 and 1 as illustrated in Eq. (29). Since the predictor variables have different ranges, the data were normalized and scaled down for development and testing. The normalized values were then scaled back to actual values to be displayed as output. Then, mixed these four normalized inputs to one ANN model input.

Subsequently, the power production regards as the output data of ANN model created. It is getting and stored on workspace window after applying the de-normalized mode function on its values to let them get back to its real values as illustrated in Eq. (30). This is continued for all variables deemed to have a significant impact on the SHP modeling. These steps can be repeated as long as relevant variables are available. For example, if in the future the SHP-is characterized, this parameter could be modeled without having to repeat the entire process. Fig.2 illustrates all stages ANN modeling process, the characteristics the test on ANN model, and evaluating the performance of the neural network.

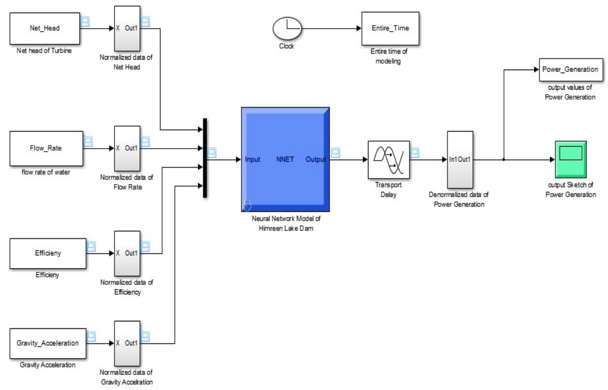

Figure 2. The architecture of the artificial neural network (ANN) modeling in the testing process

In general, the creation of ANN model should correspond exactly the actual model virtually in principles of its affections', parameters' and times' so as to get the typical model. Firstly, Entire time is regarding as the modeling time totally in simulation, which indicates to the extent of the total time for twelve years. Since there are input-output variables data has been observed daily and every day is equal to 1440 minutes. Thus, the entire time is started from 1440 minutes for the first day. It continues increasingly until it arrives at (4.5×10^6) minutes, which is equivalent to the total time in minutes. Secondly, the main reason for using the transport delay is making the ANN model to account the entire model time by increasing daily time in minutes which equals to every 1440 minutes.

III. Result and Discussion

A. Preliminary tests: training and validation of the ANN models

Preliminary tests were carried out in order to determine basic parameters needed for the soft computing model operation. Models for predicting the power generation of hydropower modeling should be evaluated in a proper way. In this study, the models constructed according to the ANN was statistically measured with the following index:

- More than 180 models were tested. The network used in the ANN method was a single and multi-layer, feed forward model, where the back-propagation distribution of error algorithm is involved. The ANN model was constructed, trained, and tested using the available test data of the AOSO.

Subsequent to the ANN model development, iteration, and testing, an investigation was undertaken to establish its efficacy as a robust system identification tool in the present hydropower generation modeling. To this end, the model output was validated against experimental data obtained for all cases of experimentation under the hydropower operation paradigm. The credibility of the developed ANN model was evaluated by the statistical metrics of R^2 and RMSE. For adjudging the model integrity, the additional absolute error metric of MAE has been chosen to represent the deterministic error in the model output.

The results of the derived SLP and MLP ANN models are shown in Table 2. According to Table 2, the best result in the ANN91 model. The total iterations in the models were set to 86 and the input layer and hidden layer(s) have nonlinear activation neurons (tansig) and output layer has linear neuron (purelin) in the network topology. The structure of ANN models is figured out in Fig.3 (a). The great predictive power of ANN91 network was illustrated in Fig.3 (b). Training, validation, and testing R^2, RMSE, MBE, and MAE of 97.941%, 97.358%, 97.771%, 0.0446, -4.1496e-04, and 0.0204 made ANN91 network become the best-fit ANN model. Thus, ANN91 network seems to be further suitable for predictions the power production.

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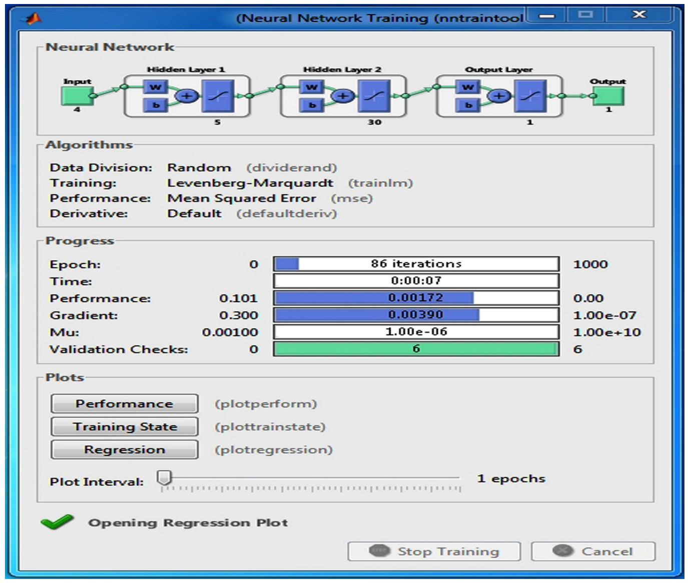

Figure 3(a). Training window of ANN91 model

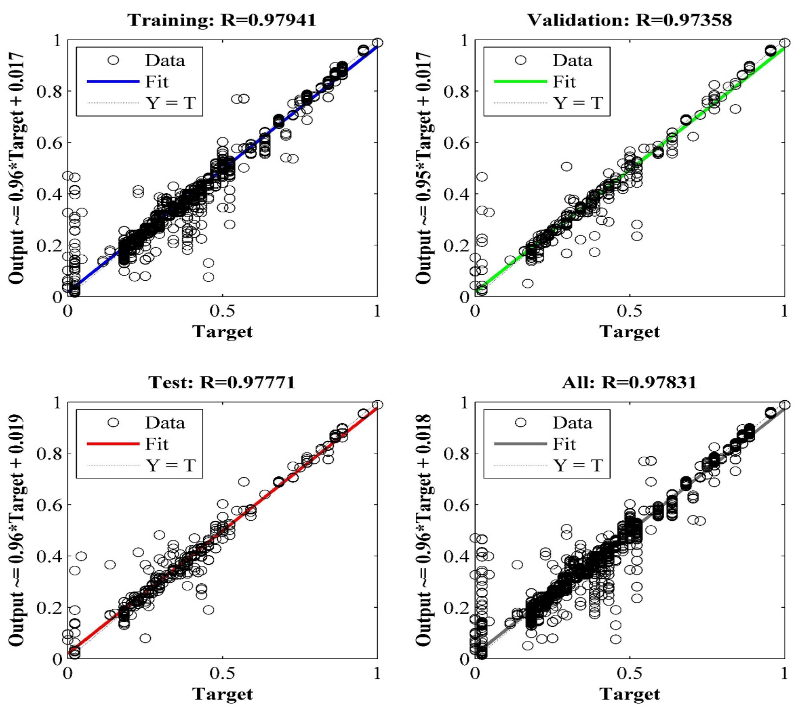

Figure 3(b). Regression plot of ANN91 model

B. Arterial Neural Network (ANN) Model

For testing and validation of the artificial neural network (ANN), the calculated values of R^2 are higher than 0.97 and RMSE is less than 0.044 that indicates adequacy and quite acceptable of the model proposed for prediction of the specific hydropower generation. The prediction ability of MLP model indicates the consistent and commendable concurrency of the predicted values with the actual values for the entire range of operation. Actually, the sensitivity and robustness of the model to predict the values of the specific power generation with an excellent accuracy were achieved.

The purpose of modeling is to perform some necessary simulation tests. These tests demonstrate the accuracy and performances of the developed ANN and FANN models. The simulation offers the possibility to have a general idea about the small hydropower plant (SHP) behavior and evaluates the simplicity of the proposed models. It is also important to know their reliability that means the precision degree that could be given to each model. The proposed model was designed in MATLAB R2015b. Since it's relatively simple with only two variable inputs (net head, flow rate) and a single output (power generation).

Response curves of modeling methods are indicated in Fig.4, in which curve 1 represents the actual observed output of the system, curve 2 is the prediction output of ANN modeling test. Simulation curves, it can be seen from Fig.4 that the output response of ANN modeling test is the highest and it's the tracking ability the best, while the counterpart of the output result of the AOSO is the worst. The tracking ability of the AOSO falls randomly and it is characterized by major fluctuations.

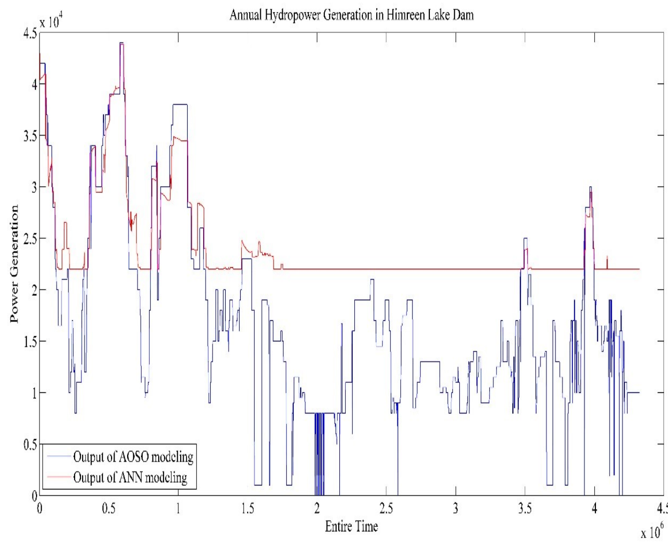

Figure 4. Hydropower generation of AOSO against ANN model

Empirical Results obtained using the ANN model with four inputs (ANN-4Parameters). The ANN model validation consisted of a qualitative comparison of the output result of ANN model against output result of actual observed of the system. Having verified that the results did not differ significantly, it was decided to use more than ten years validation set. Obviously, the difference values are owing to the flow rate is not completely used for hydropower generation. On the other hand, the main cause of low hydropower generating is to open the dam gates for agricultural irrigation purpose and power generation secondly. Nevertheless, the exact output amounts of maximum and middle of hydropower generation of ANN model are totally corresponding to the output of actual observed of the system. Meanwhile, the minimum hydropower generation values have major differences due to a very few maintenance workers that are less mature in the power generation safety and they leave the turbine works as a default with no power generation and water flow through it at very few periods. Accordingly, these difference values are represented to the deficient of hydropower generation in reality. Moreover, it is a loss in hydropower utilization. So that, how the himreen lake dam (HLD) hydropower plant can get to the best result values of power generation or at least get to the similar result of ANN model test. There is a wide necessary to create a flexible control for this purpose. Overall, the results demonstrate the robustness of neural network models regarding sample variations by showing high performance on all subsets of network performance on test data.

IV. Conclusion

In this study, a new structure of ANN models to stabilize annual hydropower operation have been proposed. The generalized ANN model was applied to describe the hydro generation in the presence of input random variables. The experimental and simulation results of the proposed ANN models show the performances and flexibilities for the modeling based on this approach. According to the hydro generation stability theory, there are some scenario tests, which illustrated in the results section. It has presented to show the exactness of the proposed ANN models compared with the output result of the AOSO model. Especially, when the proposed annual hydropower operation model is used in the closed loop. In addition, the proposed approximations permit the researchers interested in the SHP model to benefit from growth technologies in digital calculators which make synthesis robust modelling easier.

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V. Nomenclature

index

h	Actual Observed System Operator
s	Standard System Operator

parameters

Pp_i	electrical power production (KW)
g	gravity acceleration (m/s^2)
η_i	turbine effeciency
ϕ	latitude of hydropower plant (°)
lcr_i	elevation of the turbine rotor (m)
ρ	water density (kg/m^3)
R_{zw}	element (z, w) of the matrix of coefficients that relates with T(kg/m^3)
θ	constant with value 0 if 0 <Te <20 or 20 if 20 < Te < 50 (.C)
T	water temperature in the reservoir (.C)
Rfl	reservoir forebay level (m)
Rtl	reservoir tailrace level (m)
K_0	theoretical coefficient associated with the load losses in the canalintake (s^2/m^5)
Q	plant turbined outflow (m^3/s)
K_i^{ag}	aggregated coefficient of hydraulic load losses (s^2/m^5)
hll^{atm}	atmhydraulic losses due to the difference of atmospheric pressure between Rfl and Rtl (m)
bl_i	thrust bearing losses (MW)
Bt_i	turbine hydraulic thrust (N)
Dg_i	portion of thrust bearing losses referent to the generator
Dt_i	portion of thrust bearing losses referent to the turbine
Wg_i	generator weight (N)
Wt_i	turbine weight (N)
tip_i	turbine input power
top_i	turbine output power
gip_i	generator input power
gop_i	generator output power
tl_i	turbine loss
gl_i	generator loss
Nh_i^{min}, Nh_i^{max}	minmaum and maximum net head
Fr_i^{min}, Fr_i^{max}	minimum and maximum flow rate of water

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