FORECASTING HYDROPOWER GENERATION USING ARTIFICIAL NEURAL NETWORKS AND THE EFFECT OF VARIOUS ENVIRONMENTAL FACTORS FOR THE OPTIMAL OPERATION OF SPILLWAY GATES

KEMOH LUMEI
Master of Technology, Electrical Engineering Department, Delhi Technological University, New Delhi, India

ABSTRACT

This paper discusses in detail forecasting hydropower generation using artificial neural network (ANN) and the effect of various environmental factors for the optimal operation of the spillway gate. Hydropower is one of the important renewable energy sources that are produced from water stored in the reservoir with the help of the construction of dams. The main objective of this paper is to provide a forecasting framework of hydropower generation to power producers with help of accurate forecasting methods which is a key to effective operations of spillway gates, load management and the reliability of distribution systems. It is very important to forecast hydropower generation to have an optimal minimized uncertainty. Artificial neural network has the capabilities of machine learning and it is used for forecasting. This paper makes use of MATLAB for the processing of data.

Key Terms *: Artificial Neural Network (ANN), Mount Coffee Hydropower Plant (MCHPP), Liberia Electricity Corporation (LEC), Project Implementation Unit (PIU)*

1. INTRODUCTION

Liberia's procurement of diesel (heavy fuel oil) is now becoming increasingly a threat to global warming and economic constrain. Currently, the state utility (Liberia Electricity Corporation) is operating an 88 MW hydropower plant and a 30 MW diesel (heavy fuel oil) plant. The diesel (heavy fuel oil) plant runs for many days during the summer. The only alternative energy source that is much more environmentally friendly to replace the diesel generators during the summer is the MCHPP but it has serious water shortage issues. As per MCHPP being a run-of-river hydropower plant, it is characterized by no or small water storage facility. A run-of-rive basically depends on the in-flow from upstream to operate at full load capacity. The operations of MCHPP during the summer required the amount of water needed to generate power. Since run-of-river hydropower depends on constant in-flow from upstream, it is important to model a run-of-river hydropower generation schedule for optimal operation of the spillway gates. This study makes use of the hourly day-ahead forecasting method to make a generation schedule for the optimal operation of spillway gates with the help of a Matlab, ANN time series tool. The ANN is the preferred prediction tool because it has the ability to learn nonlinear relationships faster than the other prediction tools. As part of this study, the effects of environmental factors were evaluated and recommendations were made to save the environment from further hazards. The study also described the methodology used and analyzed the results obtained from the simulated model.

2. CASE STUDY AREA

A. Power House

Mount Coffee Hydropower Plant (MCHP) is the single largest hydropower plant in Liberia. The MCHPP is located in Harrisburg of Careyburg District, Montserrado County. MCHPP lies on the St. Paul River approximately 34km from Monrovia, the capital city of Liberia. The MCHPP has a run-of-river dam scheme. Due to the fact that MCHPP has a run-of-river dam scheme, plant can only operate for twelve hours for many days during the summer. By 1963, the government of Liberia got a loan from World Bank in the tone of $24.3 US million to construct a hydropower plant. The construction works of pre-war MCHP done by Monrovia Power Authority and were commissioned in 1967. The initial generating capacity was 30MW. It was produced by two generating units and the power generation was increased to 64MW the installation of two additional generating units. According to reports from those that operated the pre-war MCHPP, rebel forces took over the plant and shutoff power. With the help of Liberia's development partners, the MCHPP rehabilitation works were initiated in May 2012. Currently, MCHP has four Francis turbines. Each turbine has a rated power of 22MW and the total generating capacity of MCHP is 88MW.

Table 1 : MCHPP Pre-War and Post-War Generating Units Specification

No.	Description	Pre-War	Post-War
1	Net Head (m)	21	23.1
2	Rated Flow (m^3/s)	82	108
3	Turbine Capacity (MW)	16	22
4	Rated Speed (rpm)	112.5	142.86
5	Run Away Speed (rmp)	-	270
6	Generator Capacity (MVA)	17.64	27
7	Rated Voltage (kV)	12.47	11
8	Frequency (Hz)	60	50
9	Power Factor	0.85	0.8

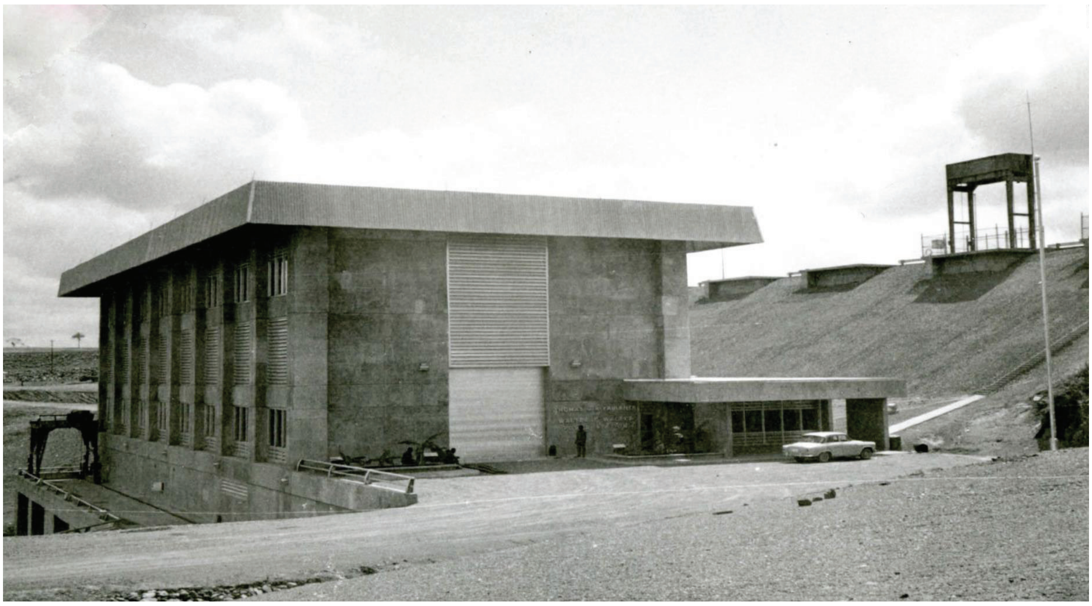

Figure 1 : Pre-War MCHPP (Source: VOITH MCHPP Training Documents)

Figure 2 : MCHPP After the Civil War (Source: LEC-PIU)

Figure 3 : Post-War MCHPP (Source: LEC-PIU)

B. Spillway Gate

A spillway gate is a hydropower structure that does not allow the level to rise and flood the area during sudden load rejection and unexpected rise in upstream flow. Spillway gates are basically located at the top of the reservoir pool. The MCHPP has ten installed radial gates and three environmental valves. Due to the flooding of MCHPP and the washing away of some civil structures during the civil unrest, the MCHPP has emergency spillway gates that are to receive excess when the spillway gates fail to operate. With the current modification of the post-war MCHPP, the powerhouse and civil structures cannot be affected by the flood like in the case of pre-war MCHPP. MCHPP's spillway gates can be controlled locally and remotely.

Table 2 : Spillway Structure Specifications

No.	Description	Values & Unit
1.	Number of Spillway Gates	10
2.	Minimum Water Level	27.4m
3.	Maximum Water Level	29.05m
4.	Number of Environment Valves	3
5.	Required Environment Flow	8.01m^3/s

Figure 4 : MCHPP Spillway Structure SCADA Control Overview

3. ENVIRONMENTAL EFFECTS

As MCHPP is a run-of-river hydropower scheme, it operates without water storage, using the flow from upstream of the St. Paul River. Typically, the water level is regulated by the spillway gates. Even though a run-of-river hydropower scheme has many benefits as compared to the impoundment dam, the small water storage can result in a smaller environmental footprint when compared to a dam with large water storage. Unlike the combustion of fuel emission, few environmental effects must be looked at. For the MCHPP, two major conditions affect the environment as it relates to spillway operations. There are changes in flow rate and access to low water.

A. Change in Flow Rate

The manipulation of the river flow rate during the operation of the spillway gates has caused a significant number of environmental effects. The changes in river flow could increase species mortality, disruption of migration and may cause an imbalance in biodiversity.

B. Access to Low Water

At MCHPP during the summer, all of the spillway gates are closed for many days due to lack of sufficient incoming water. The spillway gates are closed for the accumulation of water. The downstream side of the river only received small water from the environmental valves. For more than three months, agriculture and fishing activities affected due to the closing of the spillway gates. On the other hand, it is difficult to determine the damages caused by a run-of-river scheme comparing it to the conventional diesel generators but it is very important that we should reduce the environmental effects of the run-of-river scheme.

Figure 5 : MCHPP Spillway Flow of Water during the Raining Season (Source: LEC-PIU)

4. METHODOLOGY

This paper has made use of the Artificial Neural Network (ANN) time series MatLab tool to forecast the hourly day-ahead generation for run-of-river hydropower plant (MCHPP). This optimization technique was used to forecast hydropower generation for the optimal operations of spillway gates. The ANN is an optimization technique that is used for forecasting and estimating events in many areas of business administration and engineering. For Statistical analysis, ANN is an alternative to multiple linear and nonlinear regressions which is an information processing paradigm that is inspired by biological nervous systems. An ANN is designed for a data process, extracting patterns and detecting trends that are too complex to be identified.

A. Artificial Neural Network (ANN) Components

- NEURONS

  The ANN has artificial neurons that manic the concept of biological neurons. It receives input, combines the input with their internal state and an optional threshold using an activation function, and produces output using output function.

- WEIGHT

  The ANN has connections with each connection being assigned to a weight that represents it relative importance.

- INPUT, BIAS, HIDDEN LAYER AND OUTPUT

Basically, ANN has an input layer, hidden layer and output layer. The input layer is where all the input data are fed.

- *Input Layer* : Its job is to process all inputs data only and the data are transferred to the hidden layer.
- *Bias* : This is a special neuron added to each layer in the network. It simply stores the value of 1. The bias makes it possible to move the activation function left or right on the graph.

- *Hidden Layer* : The hidden layer is the collection of neurons that has activation function applied on it. The hidden layer is also the layer that is found between the input and output.
- *Output Layer* : The out layer collects and transmits the information accordingly in way it has been designed to display.

$$H_1 = x_1 w_1 + x_2 w_2 + x_3 w_3 + b_1 \tag{1}$$

$$H_2 = x_1 w_4 + x_2 w_5 + x_3 w_6 + b_2 \tag{2}$$

$$Sigmoid\ (H_{inew}) = \frac{1}{1+e^{-H_i}} \tag{3}$$

$$Y = H_{1new} w_7 + H_{2new} w_8 \tag{4}$$

$$Sigmoid\ (Y_{new}) = \frac{1}{1+e^{-Y}} \tag{5}$$

$$E_{total} = \sum \frac{1}{2}(target - Y)^2 \tag{6}$$

$$E_{w_i} = \frac{\partial E_{total}}{\partial w_i} \tag{7}$$

$$\frac{\partial E_{total}}{\partial w_i} = \frac{\partial E_{total}}{\partial Y_{new}} * \frac{\partial Y_{new}}{\partial Y} * \frac{\partial Y}{\partial w_i} \tag{8}$$

$$\frac{\partial E_{total}}{\partial w_i} = \frac{\partial E_{total}}{\partial Hi_{new}} * \frac{\partial H_{inew}}{\partial Hi} * \frac{\partial Hi}{\partial w_i} \tag{9}$$

$$w_{inew} = w_i - \eta * \frac{\partial E_{total}}{\partial w_i} \tag{10}$$

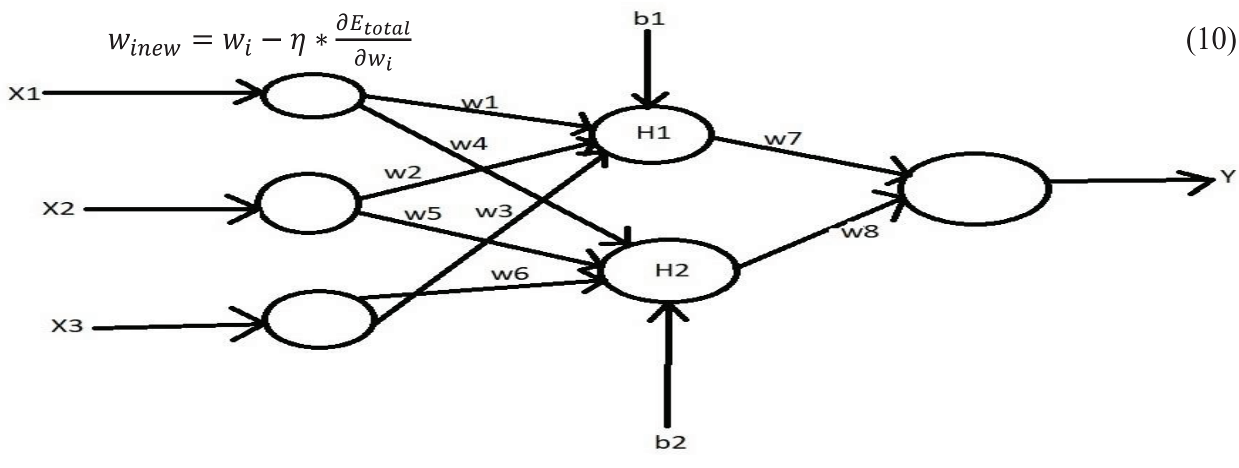

Figure 6 : ANN Structure

B. Artificial Neural Network Time Serie

The ANN time series Matlab tool gives an individual platform to solve three different nonlinear time series problems. It selects the required data for training, validation, and training. After processing the data, the ANN time series tool evaluates the mean squared error, regression analysis, error autocorrelation plot and histogram of the error and regression. The three operation models of ANN time series Matlab tool are nonlinear autoregressive with external input (NARX), Nonlinear Autoregressive (NAR) and nonlinear input-output. For the data analysis and forecasting scope of the study, the nonlinear autoregressive with external input (NARX) was used. It was used because it provides better predictions than the other two models. It uses the additional information contained in previous values of the output.

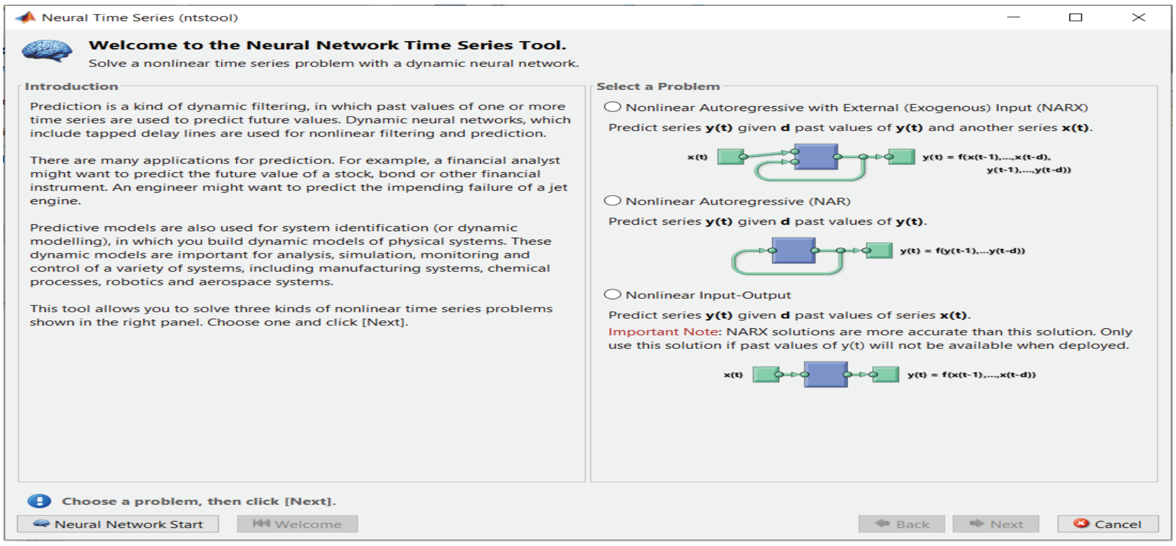

Figure 7 : Nonlinear Autoregressive With External Input (NARX)

C. Training Algorithm

The ANN Matlab tool has three training algorithm. They are: levenberg-marquard, Bayesian regularization and scaled conjugate gradient. This study make used of the levenberg-marquard combines two minimization methods. It combines the steepest desert and the Gauss-Newton method.

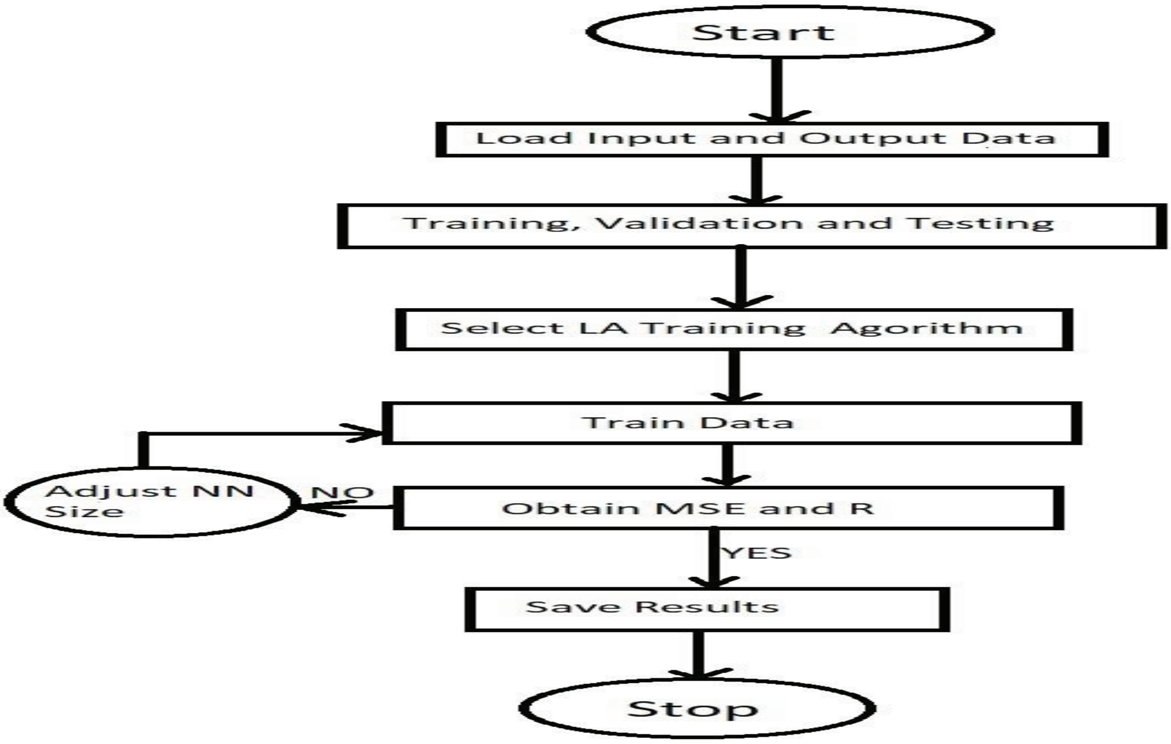

Figure 8 : ANN Flowchart

5. RESULTS AND ANALYSIS

The hydropower generation forecast was performed by using previous day data. Those predictive data that were considered for this study are stipulated in Table 3. The data was trained, validated and tested. Its analysis took into consideration performance, time state, error histogram, regression, time series response, error autocorrelation, and input-error cross-correlation.

Table 3 : Predictive data

Time	Q(m/s^3)	H(m)	Reservoir Level (m)	Tailrace Level (m)	Inflow Haindi 24h (m/s^3)	P (MW)
01:00	135.43	23.31	28.95	5.64	90.40	23.00
02:00	131.83	23.29	28.94	5.65	90.40	21.88
03:00	120.41	23.32	28.94	5.62	90.40	21.09
04:00	123.03	23.31	28.94	5.63	90.40	20.54
05:00	119.03	23.32	28.95	5.63	90.40	20.17
06:00	118.53	23.35	28.95	5.60	90.40	21.13
07:00	120.37	23.37	28.96	5.59	90.40	21.71
08:00	117.06	23.43	28.97	5.54	90.40	20.85
09:00	116.39	23.47	28.99	5.52	90.40	20.97
10:00	115.55	23.49	29.00	5.51	90.40	21.57
11:00	117.57	23.49	29.00	5.51	90.40	22.07
12:00	118.14	23.47	29.00	5.53	90.40	22.43
13:00	120.86	23.41	28.99	5.58	90.40	22.57
14:00	111.27	23.42	29.00	5.58	90.40	22.73
15:00	130.58	23.37	28.99	5.62	90.40	19.29
16:00	131.46	23.35	28.99	5.64	90.40	19.24
17:00	128.97	23.34	28.98	5.64	90.40	18.60
18:00	130.12	23.34	28.98	5.64	90.40	17.79
19:00	132.95	23.32	28.97	5.65	90.40	18.84
20:00	164.56	23.25	28.96	5.71	90.40	23.71
21:00	153.54	23.24	28.94	5.70	90.40	24.83
22:00	152.52	23.25	28.94	5.69	90.40	25.10
23:00	141.11	23.27	28.94	5.67	90.40	25.32
00:00	118.45	23.39	28.96	5.57	90.40	23.95

A. Performance

From figure 9, we can see that the training, validation error before reaching epoch 16. The best validation performance is 0.1149 at epoch 10. Training, validation, and testing were done in an open-loop. The aim is to create a network in an open-loop that can be transformed to a close-loop for multistep ahead prediction.

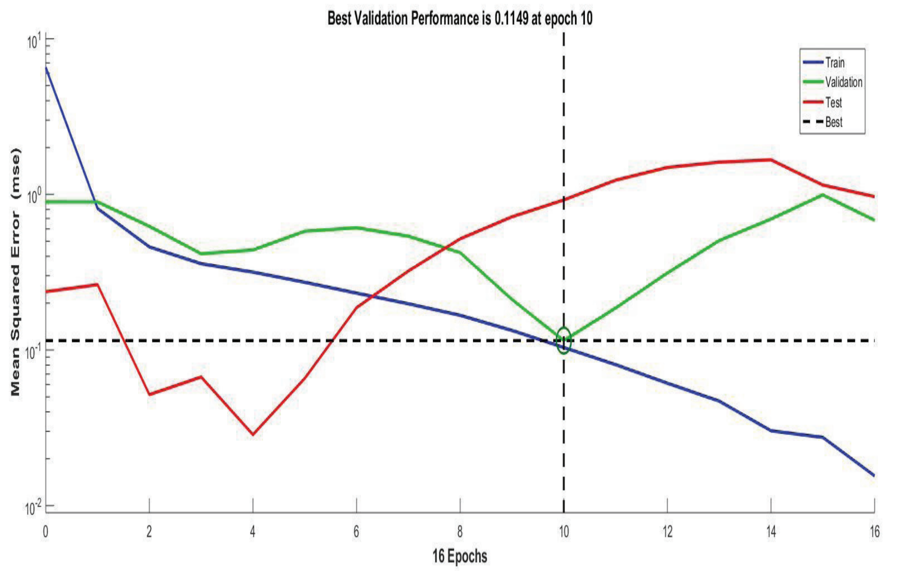

Figure 9 : ANN Performance

B. Training State

From figure 9, we can see that the training, validation error before reaching epoch 16. The best validation performance is 0.1149 at epoch 10. Training, validation, and testing were done in an open-loop. The aim is to create a network in an open-loop that can be transformed to a close-loop for multistep ahead prediction.

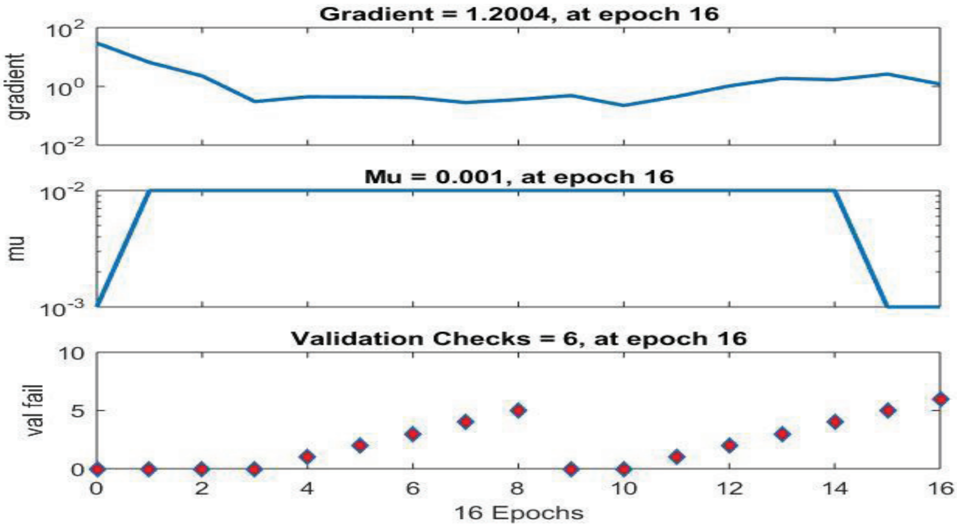

Figure 10 : ANN Training State

C. Regression

Figure 11 illustrates the regression results. It achieves a regression close to the targets and the network actual output. It can be seen that the training value is 0.99, validation is 1, and the testing value is 1. The total regression value is 0.98. Therefore, the designed model satisfies the following predictive data and it can be used for forecasting.

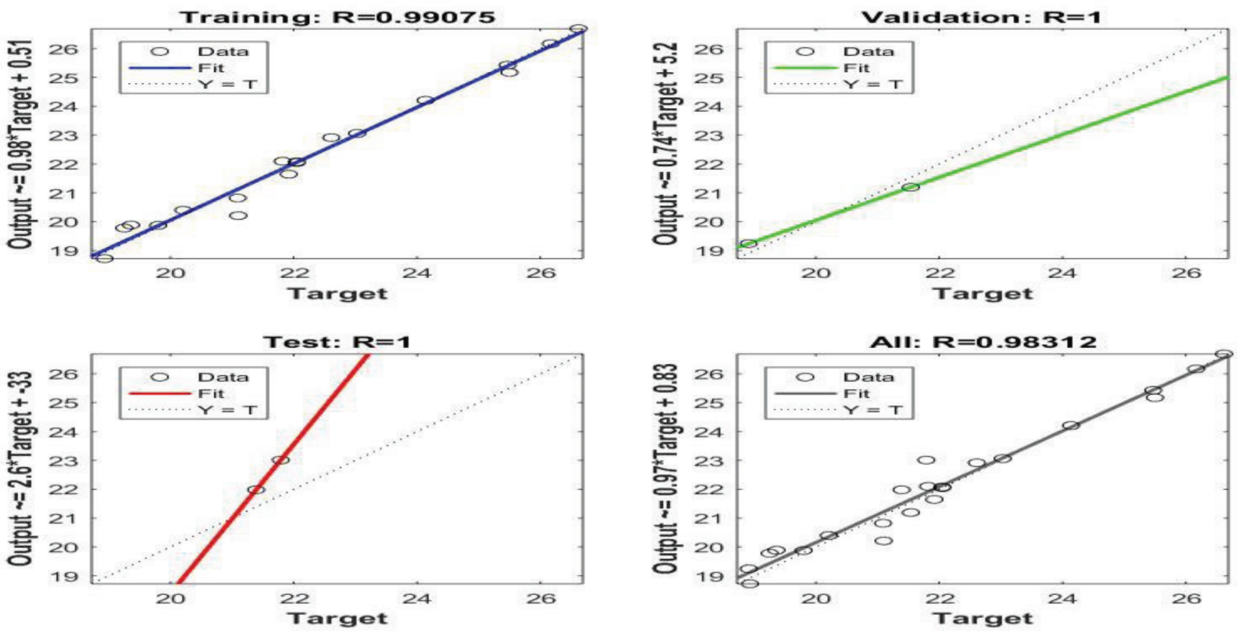

Figure 11 : ANN Regression

D. Error Autocorrelation

The error autocorrelation is shown in figure 12. Even though the prediction model has more than one nonzero values of the autocorrelation function, more than 95% of the correlation falls in the confidence limit. With what has been said, the prediction model seems to be good.

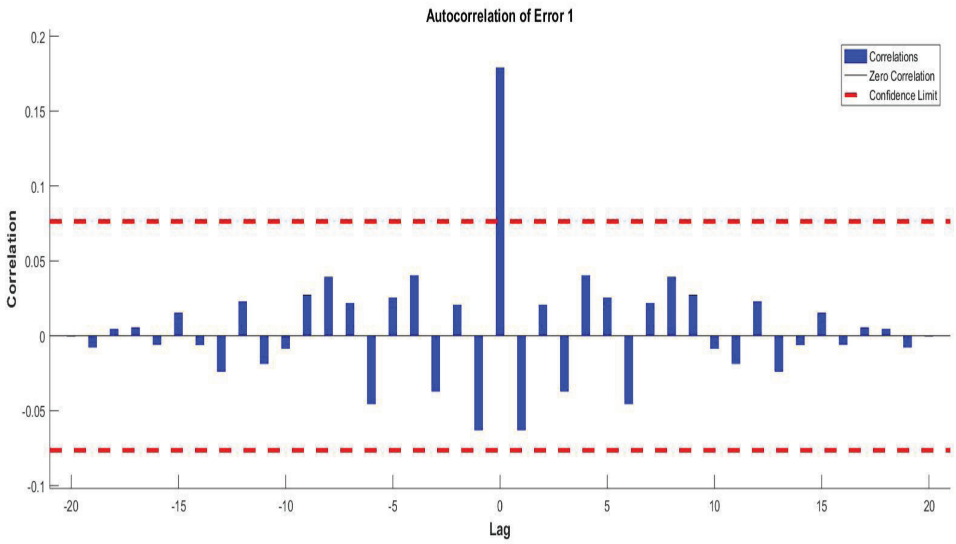

Figure 12 : ANN Error Autocorrelation

E. Input-Error Cross-Correlation

The input-error cross-correlation is been illustrated in figure 13. It shows how the errors are correlated to the input. Even though the prediction model correlations are not zero, the model is a good prediction model because all of the correlation falls in the confidence limit.

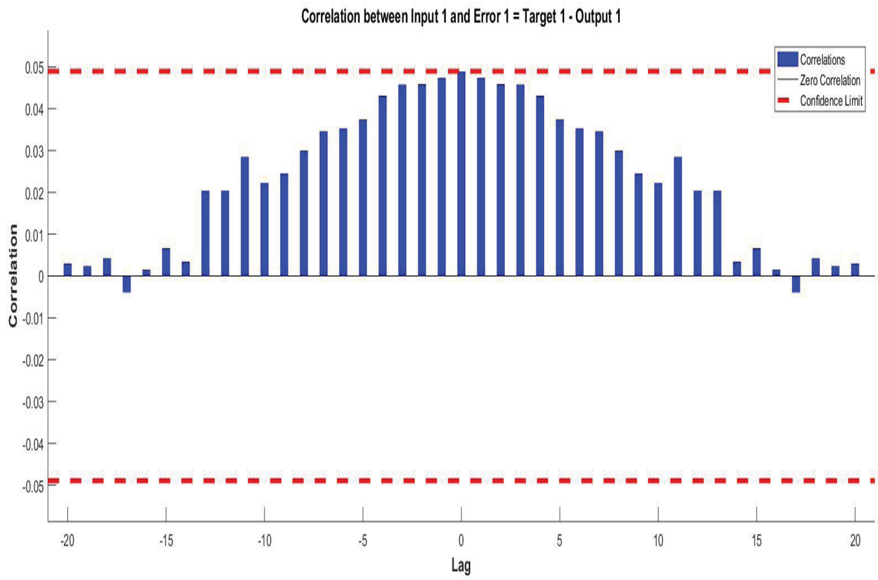

Figure 13 : Input-Error Cross-Correlation

6. RECOMMENDATION

From the studies conducted, this paper recommends the following narratives below that will address all of the issues stated above.

A. ANN Time Series Prediction Model

The ANN time series prediction model will provide a forecasting tool for a run-of-river operations and maintenance team. An accurate forecasting model like the ANN time series prediction model should be adapted for hydropower generation forecast. This will enable a run-of-river operations team to operate the spillway gates at an optimal set point to prevent unnecessary water spillage.

B. Fish Ladder, Fish Lift And Juvenile Bypass

These devices will promote and regulate the migration of fish through hydropower plant facilities like the spillway structure in a safe manner. They prevent harm from occurring in the river ecosystem. Fish and other aquatic life are provided a safe method of passage by the application of fish ladder, fish lift, and juvenile bypass system.

C. Pondage

A run-of-river with a pondage stores water for a significant period. This scheme allows the operations team to extend or shift generation as per the demand of the demand from the power grid without significantly spilling water via the spillway gates. The pondage also increase the generating capacity of the plant during the summer.

7. CONCLUSION

In nutshell, the ANN time series MatLab tool was used to forecast hydropower generation for the optimal operation of spillway gates. The studies also looked at the effect of environmental factors associated with spillway gates and recommendations were made.

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