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ON DAM WATER SPILLAGE MODELLING USING 3-2-1 NEURAL NETWORK ARCHITECTURE

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Abstract: Forecasting Dam Spillage is very important in reservoir operation and dam management. This hydro power plant is the main source of electrical energy and water, both for human consumption and for farm irrigation. When heavy rainfall occurs, heavy dam water spillage can have a great impact to the nearby communities below the dam. Monitoring the volume of dam water spillage is very crucial in the events of flood and disaster prevention programs for the safety of the communities and inhabitants especially of those living at the riverbanks. The objective of this paper is to present the use of 3-2-1 neural network architecture in forecasting the monthly dam water spillage. Three variables were used of which the average monthly rainfall and average monthly river inflow are considered the input variables and the average monthly water dam spillage is the output variable. One hundred twenty-one (121) months of data were gathered. Data from years 2013-2019 (84 months) were simulated that is 70% of the total number of data gathered and used as the training set, and the remaining 30% a total of 37 months of data records available in PAGASA and Pulangi IV HEPP were treated as the testing set that were used in determining the efficiency of the model. The Radial Basis Function Neural Network and the General Regression Neural Network were used for the calculation of the monthly dam water spillage forecast. The Root Mean Squared Error (RMSE) was used in determining the forecasting performance of the 3-2-1 architecture design. Results showed that forecasting the monthly dam water spillage volume using 3-2-1 neural network architecture model is possible and highly accurate. It also showed that the Radial basis neural network forecasts better when compared to using the General Regression Neural Network.

Keywords: Forecasting, Dam Spillage, Artificial Neural Network, Radial Basis Function Network, General Regression Neural Network

1. INTRODUCTION

Water is the most important element needed by people aside from air and land. Water is use for drinking, cooking, irrigation, and even for creating power supply. The supply of water through the interplay of wet and dry seasons varies differently, with the help of dams that store great amount of water quantities, supply of water can be secured. Dams are a multi-purpose structure that can manage the supply of water, generates mechanical and electrical energy and protection for flood threats [1]. In all the uses of these gigantic structure that holds powerful force, that when it fails pressure from store water will cause so much destruction. Dams protect flood threats but it can also be the cause of flood when it will not be manage well or fails. Many dam failures have occurred throughout U.S. history. These failures have caused massive property and environmental damages and have taken and affected thousands of lives. As the nation's dam's aged and population increases, the potentials to have deadly dam failures grow [2]. This paper aimed to come up with a mathematical model that will forecast the monthly water spillage of Pulangi IV Hydroelectric Power Plant and Agus VI Hydroelectric Power Plant, in Mindanao, Philippines, using Artificial Neural Network (ANN) to help and improve the management of these dams in decision making for environmental safety, security and disaster risk control in the region.

The Pulangi IV hydroelectric power plant or also known as Pulangi dam supports 23% of the hydroelectric power generated in Mindanao. Since the start of operation, the reservoirs associated with the power plant have received an estimated 1,500,000 m^3 of sediment annually. Of the reservoir's combined 67,000,000 m^3active capacity, 23,000,000 m^3 has been filled with silt. The unexpected siltation threatens the operation at safe conditions of the dams and their power generation, in addition to severely deteriorating predicted operational lifespan of the dam [3]. The minimum and maximum water levels at the start were raised and, in 2007, dredging work was done around the head work of the upper reservoir's head. Selective dredging in the upper reservoir commenced in 2010, and continues until 2011 [31, 32]. This amount of water does not only provide electricity in Bukidnon but also provides water for drinking and irrigation. The Pulangi dam stores not much water that causes them to release some amount of water through the 6 gates of Pulangi dam.

This causes the overflow of the Pulangi River, and because of this, some places near the river are flooded and affected the life of the simple people living there.

Valencia City barangays in the province of Bukidnon, Philippines, which are located along the banks of the Pulangi River, were ravaged by floods twice in December 2012, just 10 days apart. First on December 17 brought by tropical Storm Sendong and on December 27 when at least 1,146 families were displaced. If the Pulangi dam management just knows the most precise forecast of the water spillage and other factor that causes the flood, they can improve the management of releasing the water at a specific time. The management can now schedule as when to release water so that if rain come they can minimize the water spillage that causes the overflow of the river. The better the prediction of the water spillage of the dam the best cure the management can do to lessen the probability of the occurrence of floods to the barangays around Pulangi River. The key to forecast the water spillage is to use the best input variables that have the most significant effect.

Forecasting yields prediction about future events. It involves examination of historical data to determine the underlying information of the phenomena and use this knowledge to extrapolate the process into the future. Forecasting uses the time series historical data that determines the variable being forecasted in order to develop model for predicting future values. To forecast time series, it is essential to present the behaviour of the process by a mathematical model that can be extended into the future. It is imperative that the model will be a good representation of the observations in any local segment of time close to present. Once a valid forecasting model for the time series process has been established, an appropriate forecasting method can be developed.

Forecasting in relation to reservoir inflow, heavy water spillage, rainfall intensity, reservoir water level, short term flood monitoring were successfully studied in [4, 6, 10]. Regression analysis, stochastic analysis, artificial neural network (ANN) architectures were the methods used in forecasting which provided a high level of efficiency [8, 9, 11, 12, 16, 17]. The Talib and Hasan [16] study showed the possibility of forecasting one (1) month ahead prior to dam spillage using a supervised neural network. Hyperbolic tangent was used as the estimator of the 3-2-1 neural architecture model. The variables that were selected for inputs include monthly rainfall, monthly inflow and dam release. The Kumarasiri and Sonnadra [13] study is using neural network rainfall forecasting which is one month ahead. Results were reasonably successful with a success rate of 58.33% within a ± 50mm error limit. Ababaei et al [17] studied the suitability of using different types of artificial neural networks in analyzing daily inflow by simulation. Results revealed the potential models: Elman Network, Radial Basis Neural Network (RBN) and General Regression Neural Network (GRNN) as suitable tools for simulating the daily reservoir inflow.

Basically, the advantages of neural networks are that they are able to represent or model both linear and non-linear relationships. Many researchers compared statistical methods to ANNs [14, 15] and found out that ANNs perform better compared to the traditional Multiple Regression and other classes of statistical modeling. Since ANNs are more flexible, it is more suitable for prediction with more precise and accurate results.

The study will forecast the total volume of water spillage that will be added to the river using artificial neural 3-2-1 network model. By this model, the dam forecasting management system will have another tool of computation to help forecast the possible volume of water spillage. With this, the people living in the nearby villages will be informed by the municipal government when it was time for them to evacuate from their houses in order to avoid accidents. The local government units or any disaster risk management unit will also benefit since they can prevent or reduce the total possible damage that might happen in their municipality with regards to agriculture and infrastructure using this forecasting model. This also attempts to develop a forecasting model that will determine the dam water spillage in any hydro power plant using the rainfall and river inflows as the contributing factors of dam water level rise.

The specific objective of this study is to meet the following expectations:

(*i*) Identify the performance of the 3-2-1 neural network architecture model when using the Radial Basis Function Neural Network and General Regression Neural Network in forecasting water spillage; and

(*ii*) Test and validate the efficiency of using both the Radial Basis Function and the General Regression Neural Network for water spillage.

2. REVIEW OF RELATED LITERATURE

Artificial Neural Network (ANN) is a simplified model that mimics the signal processing system of human brains [19, 23]. ANN is capable to predict possible relationships of variables from a large and complicated data through learning by experiences [20]. Subsequently, ANN is widely used in modeling for complex nonlinear phenomena especially in practical engineering problems [30]. In the practice of hydrology measurement, forecasting accuracy of reservoir inflow and evaporation is major concern to attain successful decision making for reservoir operation. Reservoir inflow pattern is highly nonlinear, complex and highly stochastic, hence selecting a reliable predictive model is crucial [19]. Thus, many researchers implemented the reservoir inflow forecasting using ANN-based model and achieved many promising results. ANN-based models provided great potential in inflow forecasting application [20].

Several studies were conducted for dam spillage forecasting using ANNs. Abdulkadir, Salami, Sule, & Adeyemo [18] forecasted the future storage of the hydropower reservoirs in Nigeria using ANN model with monthly historical data such as reservoir inflow, turbine releases, reservoir storage and evaporation losses for Jebba, Kainji and Shiroro hydropower dams. The obtained values of correlation coefficient between the forecasted and observed reservoir storage suggested that the model fairly fit the data defined by the variables and can subsequently be employed for prediction of reservoir storage for operational performance. Sulafa [27] used ANN model to simulate flows at Dongola Station and predict the possibility of flooding. The results indicated that ANN offers a reliable means of detecting the flood hazard in the River Nile. The study of Aljabi [18] used ANN to forecast the monthly water release for Haditha Dam. Out of the principal inputs which are used to compute monthly release, the results showed that reservoir storage has the most significance followed by water spillage and rainfall with relative importance of 40.8%, 21.96%, and 16.12% respectively. Ramli, Fazlina, Abdmanan and Zainazian [25] modeled the water level at downstream station using the gathered data at the upstream and downstream station of a river. The back propagation neural network (BPN) was employed with an extended kalman filter introduced at its output. This revealed a significant improvement to the prediction and tracking performance of the actual flood water level. Moreover, Talib and Hasan [28] study showed the possibility of forecasting one month ahead prior to dam spillage using a supervised neural network and a 10-year hydrological dataset of Ahning Dam in Northern Malaysia at Phedu-Muda area. Hyperbolic tangent was used as the estimator of the 3-2-1 neural architecture model with input variables, which include monthly rainfall, monthly inflow and dam release.

Several types of ANN methods can be utilized for inflow and evaporation modeling. Radial basis function is viewed as one of the most commonly used kernel functions because it has better generalization ability compared to other kernel functions [23]. Sim, Burn & Tolson [26] addressed the design of a monitoring station as an early warning station for a riverine source of drinking water intake on the Grand River in southern Ontario using a probabilistic modeling technique. The objectives of the design involve maximizing the probabilities of detection and of having a threshold amount of warning time. Similarly, Golez [5] characterized the mean integrated squared prediction errors using RBFN as predictor of chaotic dynamical system. Specifically, Gaussian and exponential kernel functions are use as activation functions for hidden layer and use Nadaraya-Watson Estimator to predict future values. The results showed that MAPE using RBFN are consistently decreasing as the number of samples decreases and consistently increasing as the number of predicted values increases.

Basically, the advantages of neural networks are that they can represent both linear and non-linear relationships. Numerous studies investigated the difference in performances among ANN models and other similar forecasting methods. Niu et. al [23] examined the performances of four effective methods in deriving the operation rule of Hongjiadu hydropower reservoir including Multiple Linear Regression (MLR), ANN, Extreme Learning Machine (ELM), and Support Vector Machine (SVM) with the conventional Scheduling Graph Method (SGM) approach as the benchmark yardstick and the dynamic programming method to optimize and develop those models. Evaluation of the performances of these methods as well as the average power generation and generation guarantee rate was conducted. The findings indicated that ANN, ELM, and SVM provide better simulation performances than SG M and MLR. Thus, the artificial intelligence methods are promising tools in deriving the operation rule of a hydropower reservoir. Oye & Hannatu [24] also conducted a review for ANN as used in flood prediction and concluded that ANN has the room to extend the application. Ababaei, Sohrabi, Mirzaei, Araghinejad, & Ahmadizadeh [17] studied the suitability of using different types of ANN in analyzing daily inflow by simulation. Results revealed the potential models: Elman Network, RBFN and generalized regression neural network(GRNN) as suitable tools for simulating the daily reservoir inflow. Mishra, Gupta, Pandey, & Shukla [22] presented the application and comparison of ANN approaches and autoregressive (AR) method to predict daily stream flows at Çifteler station in the Sakarya River. ANN methods such as feed-forward back propagation neural networks (FFBN), RBNN and recurrent neural networks (RNN) were selected in modeling hydrological time-series and generating synthetic stream flows. Results revealed that RNN model yields the best result with a determination coefficient of 0.9991.Wang & Sheng [29] introduced the application of GRNN model to forecast annual rainfall and compared the results with the back propagation (BP) neural network and regression analysis method. Comparing GRNN with the traditional linear model and BP neural networks, the former has better accuracy with smaller prediction error. Also, Coskun, Cigizoglu & Maktav [21] concluded that GRNN perform better than FFBN in monthly mean flow forecasting. Indeed, ANN is a successful and effective forecasting tool for widespread applications.

3. DESIGN AND METHODS

This study uses an artificial neural network, a mathematical model motivated by biological neural networks. A neural network is composed of an interconnected group of artificial neurons, which processes information using a connectionist approach to computation. Neural network, in most cases, is an adaptive system that changes its structure during a learning phase. Neural networks are useful to model complex relationships between inputs and outputs or to find patterns in a mass of data. An artificial neural network, in particular, is an interconnected collection of nodes, akin to the vast network of neurons in the human brain [8]. A simple neural network structure, as seen in Fig. 3.1, contains an input layer, hidden layer and an output layer. An input layer refers to input variables used in the architecture, the hidden layer where the input variables are being processed to produce an output and the output layer provides the response of the network.

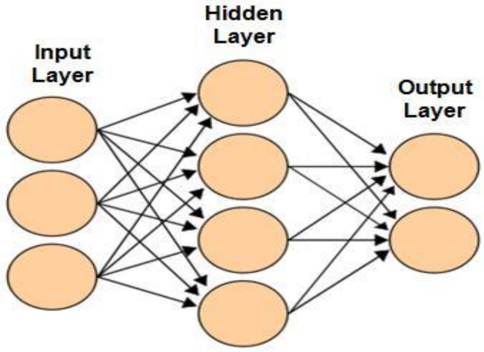

Figure 3.1 Architecture of Artificial Neural Network [9]

There are lots of possible neural architectures [8, 9, 11, 12], but this paper uses Radial Basis Function Network (RBFN) architecture with two (2) input variables and one (1) output variable. The architecture's performance is utilized in the forecasting of water spillage. The use of RBFN architecture was already proven that radial basis function network is suitable for chaotic dynamic systems and because RBFN architectures have high performance in any sort of model (linear or nonlinear) [8, 9, 11, 12]. A radial basis function network (RBFN) is an artificial neural network that employs radial basis functions as activation functions. The network has its output as a linear combination of radial basis functions of the inputs and neuron parameters. Radial basis function networks are applied for function approximation, time series prediction, and system control.

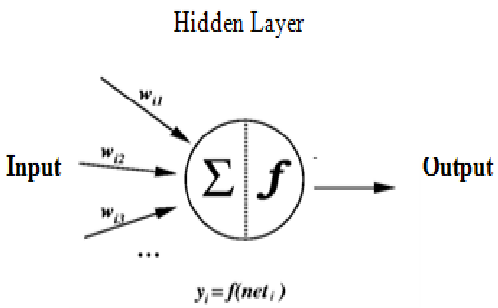

Figure 3.2 Neural Network Processing System

A generalized regression neural network (GRNN) was also used for the calculation of the monthly dam water spillage forecast. It is often used for function approximation. A GRNN is a variation of the radial basis neural networks based on kernel regression networks [33, 34]. A GRNN does not involve an iterative training procedure as back propagation networks. It estimates any arbitrary function between input and output vectors, illustrating the function approximation directly from the training data set [35].

To determine the performance of the 3-2-1 neural network architecture model when using the Radial Basis Function neural network and the General Regression Neural Network in forecasting water spillage, the following model for error analysis is applied.

(*i*) Root Mean Squared Error (RMSE)

To test the efficiency of the artificial neural network model, 90 percent of the data gathered is used as the training set, while the remaining 10 percent is treated as the testing set. The Root Mean Squared Error (RMSE) was used in determining the model error [11, 17]. The lesser the error between the true value and calculated value the more efficient the model is.

The Root Mean Squared Error is calculated using the equation below,

$$RMSE = \frac{1}{\bar{Y}_t}\sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2} \qquad (1)$$

where $\bar{Y}t$ is the mean of the observed values.

3.1 Data Gathering

All the three variables; amount of rainfall, average inflow and dam water spillage, needed were based between the calendar years 2008-2012 records of PAGASA in the Municipality of Maramag and records of Pulangi IV HEPP, both from the province of Bukidnon, Philippines. Data from years 2013-2019 (84 months) were simulated that is70% of the total number of data gathered and used as the training set, and the remaining 30% a total of 37 months of data records available in PAGASA and Pulangi IV HEPP were treated as the testing set that were used in determining the efficiency of the model.

3.2 Simulation Algorithm

The following procedure was performed to forecast the water spillage using the MATLAB software programming language.

Step 1 Simulate data for the years 2013 – 2019 that is 84 months using the data gathered from PAGASA and Pulangi IV HEPP for the years 2008 - 2012.

Step 2 Input the training sets of the data, (1) Rainfall data and (2) Inflow data.

Step 3 Input the testing set of the data, (3) water spillage.

Step 4 Compute the values of water spillage using the Matlab programming language, applied to the equations provided by the 3-2-1 ANN models.

Step 5 Compute the gap between the actual and forecasted values of water spillage using Root Mean Squared Error (RMSE)

3.2a Using MATLAB Function, Train Radial Basis Function Network

We considered 3 sets of variables and the output is the volume of water spillage. Below were the procedures on simulating RBFN in MATLAB:

Step 1. Simulate the data set for rainfall, inflow and spillage.

Step 2. Input the training.

Rainfall= $[x_1, x_2, x_3, \ldots, x_n]$

Inflow= $[x_1, x_2, x_3, \ldots, x_n]$

Step 3. Input the target set.

Spillage $[x_1, x_2, x_3, \ldots, x_n]$

Step 4. Use syntax of RBFN.

```
traningset=[rainfall;inflow];

targetset=(spillage);

rbfn1=newrb(trainingset,targetset,0.01)
```

3.2b Using MATLAB function, Train Generalized Regression Neural network

We also considered the 3 sets of variables and the output is the volume of water spillage.

Step 1. Simulate the data set for rainfall, inflow and spillage.

Step 2. Input the training.

Rainfall= $[x_1, x_2, x_3, \ldots, x_n]$

Inflow= $[x_1, x_2, x_3, \ldots, x_n]$

Step 3. Input the target set.

Spillage $[x_1, x_2, x_3, \ldots, x_n]$

Step 4. Use syntax of RBFN.

traningset=[rainfall;inflow];

targetset=(spillage);

grnn1=newgrnn(trainingset,targetset,0.1)

3.2c Validate results against actual data from Pulangi IV using RMSE

The researchers validated the GRNN and RBFN using 30% of the data to forecast water spillage. After water spillage was forecasted we used RMSE to solve for the error against the actual water spillage. Below were the steps that are followed during forecasting and validation against the actual water spillage:

Step 1. Input new variables from 30% of the data.

newrainfall= $[x_1, x_2, x_3, \ldots, x_n]$

newinflow= $[x_1, x_2, x_3, \ldots, x_n]$;

newinput=[newrainfall;newreservoir];

step 2. Use the RBFN1 and GRNN1 that were trained using set 1 of data.

For GRNN1

forecast=sim(grnn1,newinput);

For RBFN1

forecast=sim(rbfn1,newinput);

4. MAIN RESULTS

The forecasting performance of the 3-2-1 neural network architecture model can be identified using the Root Mean Squared Error (RMSE). A lesser RMSE value generates a more accurate forecasting model. To test and validate the efficiency of using both the RBFN and the GRNN, an efficient model, the RMSE must have a very small value close to zero. Below are the data variables, figures and tables that will satisfy the objectives of this study.

Based on the Figure 3.2, the three (3) variables needed in the forecasting are (1) volume flow rate of water inflow, (2) rainfall and (3) water spillage. The two (2) input variables are: (1) the volume flow rate of rainfall and (2) water inflow. The output variable is the volume flow rate of water spillage.

The figures 4.1, 4.2 and 4.3 below, represents the monthly data points (x-axis), rainfall in mm, water inflow in millions cu. meter, and spillage in cu. meter per hour.

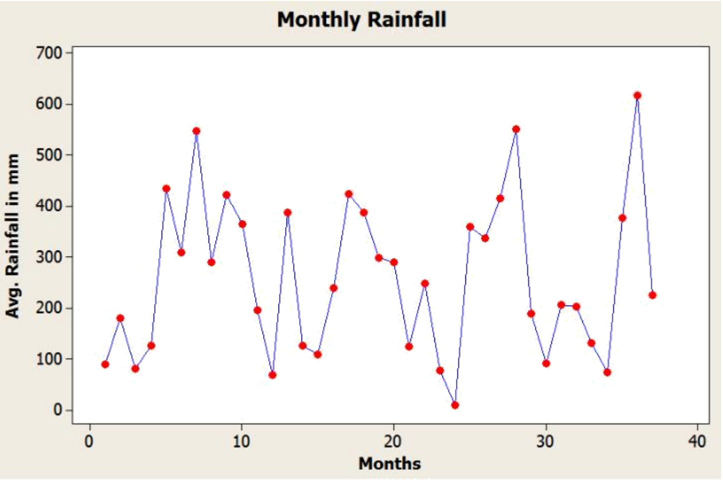

Figure 4.1 Monthly average rainfall data in millimeters

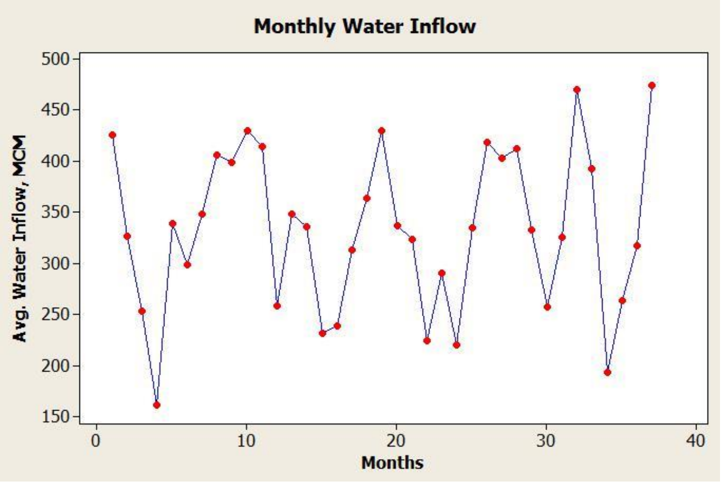

Figure 4.2 Monthly average water inflow in millions cubic meter, MCM

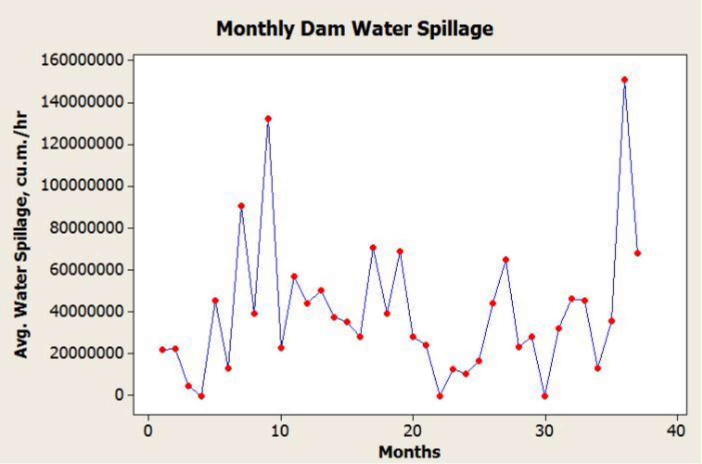

Figure 4.3 Monthly average Dam spillage in cubic meter per hour

Table 4.1 showed the results of Forecasting Water Spillage using Standard Radial Basis Function Neural Network and using the General Regression Neural Network. The difference in values showed that using the standard RBFN provide better results rather than using the GRNN.

Table 4.1 Forecasted water spillage using standard Radial Basis Function Neural Network and General Regression Neural Network

Month	FORECASTED WATER SPILLAGE	
	Standard GRNN in cu. m/hr	Standard RBFN in cu.m/hr
1	21,882,114	21,880,000
2	22,496,462	22,500,000
3	4,826,868	4,830,000
4	0	0
5	45,673,868	45,670,000
6	13,051,483	13,050,000
7	90,543,775	90,540,000
8	39,082,901	39,080,000
9	132,277,310	132,280,000
10	22,831,221	22,830,000
11	57,104,258	57,100,000
12	44,265,018	44,270,000
13	50,172,028	50,170,000
14	37,427,203	37,430,000
15	35,174,285	35,170,000
16	28,294,243	28,290,000
17	70,593,229	70,590,000
18	39,322,765	39,320,000
19	69,163,465	69,160,000
20	28,325,682	28,330,000
21	24,394,399	24,390,000
22	0	0
23	12,822,524	12,820,000
24	10,570,204	10,570,000
25	56,333,212	56,330,000
26	6,197,028	6,200,000
27	16,701,103	16,700,000
28	44,243,894	44,240,000
29	65,032,097	65,030,000
30	23,286,347	23,290,000
31	28,357,318	28,360,000
32	0	0
33	32,371,851	32,370,000
34	46,544,377	46,540,000
35	45,419,010	45,420,000
36	13,255,742	13,260,000
37	35,740,643	35,740,000

The values in Table 4.1 were generated using the Matlab Neural Network Toolbox function for standard RBFN and GRNN. Both RBFN and GRNN are embedded in a Matlab Neural Network code standard RBFN and GRNN Architecture where the Estimator was hidden in a neural network hidden layer. The forecasting functions cannot be determined due to the neural network characteristics which hide the processing of every estimator's used inside the hidden layer of neural network architectures. Table 4.1 shows the output of the forecasted values using the RBFN and the GRNN.

Table 4.2 shows the RMSE in determining the performance of using the standard RBFN and General Regression Neural Network in forecasting Dam water spillage using the 3-2-1 neural network architecture.

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Table 4.2 Comparison between RMSE of RBFN and GRNN

RMSE	
Standard RBFN	GRNN
0.731725733	0.731747943

Table 4.2 shows the consistency of Standard RBFN as the efficient model as compared to using the General Regression Neural Network.

5. DISCUSSIONS

The standard RBFN and the GRNN were used in the calculation using Matlab, since it was already proven to more accurate and suitable for chaotic dynamical systems [5]. The figures 4.1, 4.2 and 4.3 showed the dynamical behavior of rainfall, water inflow and water spillage. These meant that using the ANN will simply predict the total volume flow rate of water that the hydroelectric power plant spill. Rainfall, water inflow and water spillage are examples of dynamical systems which can be forecasted using the RBFN.

Table 4.2 provides the RMSE which showed that standard RBFN is a more efficient method as compared to General Regression Neural Network. Forecasting chaotic dynamical events, using RBFN are very advisable for they give an acceptable error between the actual and forecasted values.

6.CONCLUSIONS

Forecasting monthly dam water spillage using rainfall and water inflow as inputs is possible by the help of Radial Basis Function Neural Network (RBFN) and General Regression Neural Network (GRNN). RMSE showed that our standard Radial Basis Function 3-2-1 architecture model provides forecast for dam water spillage at a greater accuracy. This result implies that the standard Radial Basis Function 3-2-1 network model was able to forecast the dam volume of water spillage using the actual rainfall and river inflows data as input variables. Meanwhile, the design 3-2-1 network model provides high efficiency in forecasting Dam water spillage. Thus, the efficiency of the Artificial Neural Network model using standard RBFN and GRNN as predictor is acceptable at high accuracy.

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