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Application of Artificial Neural Network (ANN) for Reservoir Water Level Forecasting

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Abstract: ***Future water level forecast helps in knowing the water storage capacity of reservoir which can further be employed for irrigation, water supply, hydropower, etc. These soft computing techniques can map an input-output pattern without the prior knowledge of the criteria that influence the forecast procedure. Amongst the all, the artificial neural network (ANN) is one of the most accurate models that is used in water resource management. The principal inputs that are used to compute water level at t+1 time are: Inflow, water level at t time and released water. The statistics parameters room mean square error (RMSE), coefficient of correlation (R), coefficient of determination (R^2) and discrepancy ratio (D) were used to get best model out of three alternatives. The objective is to define the ANN model by applying different types of network tools like Feed Forward distributed time delay, layer recurrent and NARX on a set of input data to forecast the 10 day ahead water level for the case study, Sukhi Reservoir Project, Gujarat, India. The study reveals that, among the three algorithms applied, ANN using Feed Forward distributed time delay is an appropriate predictor for real-time Water Level forecasting of study area.***

Keywords: Artificial Neural Network, Inflow, Release, Reservoir, Water Level forecast.

1. Introduction

The water resources mainly deal with the reservoir which provides effective water storage which can be employed for irrigation needs, water supply, hydropower, and flood - drought control. By knowing the reservoir level the stored water can be effectively used and the desired performance can be obtained. The parameters that influence the reservoir level (e.g., inflow to reservoir, water storage in reservoir, water release from reservoir, evaporation, soil moisture and infiltration) represents uncertainties and it must be considered in water resource operation. In reservoir studies, forecasting is normally forecasting of water level.

Reservoir plays a vital function at various times and for different purposes such as water for hydropower generation, irrigation supply, mitigating disastrous environmental effects and impacts, as well as ensuring flood mitigation and as an insurance during periods of drought etc. Information regarding reservoir water level, is necessary in the analysis and design of several water resources projects such as dam construction, irrigation needs and flood control.

An artificial neural network (ANN), usually called neural network (NN), is a computational or mathematical model that is inspired by the structure or functional aspects of biological neural networks. When the underlying relationship between data is unknown, ANN proves to be powerful tool. ANN can easily identify and learn interconnected patterns between input data sets and corresponding target values. After training the data, ANN can be applied on a set of new independent input data to predict the outcome. Thus they are ideally suited for the modeling of hydrological data which are known to be non-linear and complex. ANN has great ability in foretelling modelling i.e., all the characters describing the unknown situation can be presented to the trained ANN, and then prediction of hydrological values is surefire. ANN has had wide application in many spheres of life. According to Maier and Dandy, in recent years, Artificial Neural Networks (ANNs) have become extremely popular for prediction and forecasting in a numeral of areas, including water resources, environmental science, power generation and as well as medicine and finance. The utility of artificial neural network models lies in the fact that they can be used to conclude a function from observations only. This is mainly useful in areas of applications where the complexity of the data or task makes the design of such a function by hand impractical.

Some research carried out for water level forecast using ANN. Mashudi [5] reviewed the use of Neural Networks (NN) as a potential means of more accurately forecasting water demand in the Citarum River Basin. Neural Networks have the capability to recognise non linear patterns when sufficiently trained with historical data. The study constructs a NN model of the cascade, based on back propagation Networks (BPN).Data representing physical characteristics and meteorological conditions in the Citarum River basin from 1989 through 1995 were used to train the BPN. Nonlinear activation functions (Sigmoid, tangent, and Gaussian function) and hidden layer in the BPN were chosen for study. Alvisi et al. [1] studied three data-driven water level forecasting models. The One that is based on the artificial neural networks approach, while the rest of two models are based on the Mamdani and the Takagi-Sugeno fuzzy logic approaches, respectively. All of them are parameterized with reference to flood events alone, where water levels are higher than a particular threshold. The same input and output variables are used for the analysis of the three models. However, in order to evaluate their capability and to deal with different levels of information, two different input sets are deliberated. The former is characterized by significant time and spatial aggregated information of rainfall, while the latter considers information related to rainfall that is more distributed in space and time. The feature groups comprising datas of Reservoir water levels, rainfall in the catchment, evaporation, discharges from rivers Malewa and Gilgil and one pair of time harmonics were used to develop neural network models by Ondimu and Murase [7] and it was further used to forecast water levels for Lake Naivasha in Kenya. Each feature group comprises of Six elements. Some feature groups were compacted using the Karhunen–Loeve Transform (KLT) to reduce their magnitudes. The neural network models developed that were able to forecast the reservoir levels very effectively for the lake for consecutive four months after a given month and given data for consecutive six months prior to the month. It was found that the ability of neural network to forecast the reservoir level accurately increases with the increase in the number of feature groups. Data compression generally reduced the size and computation time of the models. Okoye & Igboanugo [6] states that Poor electricity generation in Nigeria is a very dangerous problem. Accurate prediction of water levels in dams is very important in power planning. Optional power planning helps in ensuring steady supply of electric power to the consumers. The aim of the study is to develop artificial neural network models for predicting water levels at Kanji Dam, which supplies water for hydropower generation to Nigeria's largest hydropower generation station. It comprises taking of ten-year record of the daily water levels data of the dam from 2001 to 2010. The regular water level data were used to develop neural network models and an Autoregressive Integrated Moving Average (ARIMA) model to get the daily water levels obtained in the year 2010. The results show that the forecast accuracy of the neural network models increased with increasing input, but after the four-input, the accuracy of model started to decline. The four-input neural network model had the lowest relative error of 0.062 percent while the highest relative error was obtained by single-input model of 0.237 percent. The ARIMA model with relative error of 0.039 percent had the greatest prediction. Generally, the model’s predictions were good, but the neural network models was simpler to build that involve little mathematics. The developed models will be very useful in power planning in Nigeria's hydropower stations for more efficient and optimal power supply.

2. Study Area

Sukhi Reservoir project, one of the major Water Resources projects envisaged, constructed and developed by Govt. of Gujarat at the confluence of river Sukhi and Bharaj river near village Sagadhra and Khos in Pavijetpur and Chhota-Udepur Taluka of Vadodara District in Gujarat State, India. It is situate at latitude of 22° 26’ 00” N and longitude of 73° 53’ 00” E. Vadodara district lies between 72.51`to 74.17` Eastern Longitude and 20.49` to 22.49` Northern Latitude on the World Map. Geographical area of the district is 7,555.55 sq. km

Figure 1: Sukhi Reservoir

Sukhi Reservoir has its catchment area of 25.90 sq.km in Madhya Pradesh and 385.91sq. km in Gujarat, thus having a total catchment area of 411.81sq. km. The hydrological data such as Inflow, Reservoir level and release data of 23 years are collected.

3. Methodology

The development of Artificial Neural Networks (ANN), which perform nonlinear mapping between inputs and outputs, has recently provided another approach to forecast Water Level. ANN were first developed in the 1940s (Mc Culloch and Pitts, 1943), and the development has experienced a revival with Hopfield’s effort (Hopfield, 1982) in iterative auto-associable neural networks. In current decades, the developed algorithms have helped to overcome a number of limitations in the traditional networking methods, making the practical applications of ANN more significent. Based on the structure of the neural networks and the algorithm developed, various neural network models have been studied and targeted to solve different sets of problems faced by researchers.

In recent days, Neural networks have been widely applied to model many of nonlinear hydrologic processes such as water level, rainfall-runoff, stream flow, groundwater Management, water quality simulation and rainfall forecasting.

Reservoir water level is influence by a number of factors such as inflow, water level and release. In this study data from January 1990 – October 2013 has been collected. Inflow data along with release and the current reservoir water level (*t*) are used as the input data and the reservoir water level at time *t+1* is used as the target. The model was prepared using three alternative ANN models i.e. Feed forward distributed time delay, Layer recurrent and NARX.

There are four main parts of reservoir namely, upstream, reservoir catchment, the spillway gate, and downstream (Figure 2).

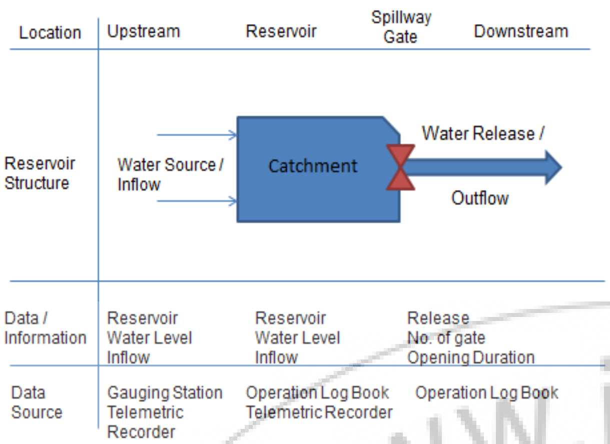

Figure 2: Conceptual model of reservoir system.

As shown in Figure x_2... x_n represent the input ne w_1, w_2... w_n represent the connection weights, *s* represent the total weighted input signals, and *f(s)* is the activation function and *y* is the output. Figure 3 shows the simple neural network model.

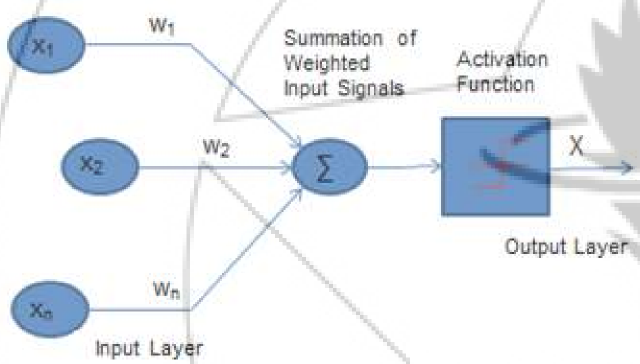

Figure 3: Simple neural network model

The hidden units use the sigmoid activation function. As application is for time series prediction, supervised learning is used. Seventy (70%) percent of the data was used for training, while thirty (30%) percent was used for testing and validation. The number of epoch was set to 1000. Given an input vector (X = (x1; x2)), the activations of the input units are set to (a1; a2) = (x1; x2) and the network computes to:

$$In_i = \sum_{j=1}^{n} W_{j,i} a_j \quad (1)$$

$$a_i = g(In_i) \quad (2)$$

For the single input network shown in Figure 4, the network computes to:

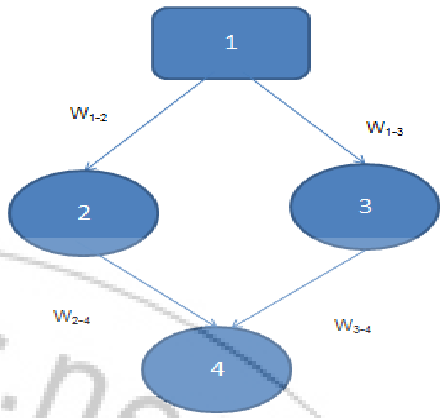

Figure 4: Single input neural network model

$$a_4 = g(W_{2,4}a_2 + W_{3,4}a_3) \quad (3)$$

$$a_4 = g(W_{2,4}g(W_{1,2}a_1) + W_{3,4}g(W_{1,3}a_1)) \quad (4)$$

For the two-input network shown in Figure 5, the network computes to:

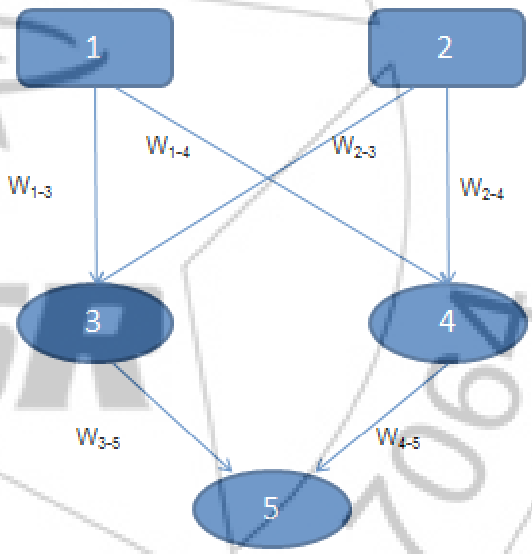

Figure 5: Two input neural network model

$$a_5 = g(W_{3,5}a_3 + W_{4,5}a_4) \quad (5)$$

$$a_5 = g(W_{3,5}g(W_{1,3}a_1 + W_{2,3}a_2) + W_{4,5}g(W_{1,4}a_1 + W_{2,4}a_2)) \quad (6)$$

For the single input architecture, the input vector is X = (X_{t-367}), for the two input architecture, the input vector is X = (X_{t-367};X_{t-732}), for the three input architecture, the input vector is X = (X_{t-367};X_{t-732};X_{1097}), for the four input architecture, the input vector is X = (X_{t-367};X_{t-732};X_{1097};X_{t-1463}) while for the five input architecture, the input vector is X = (X_{t-367};X_{t-732};X_{t-1097};X_{t-1463};X_{t-1828}).

The learning process uses the sum of squares error criterion E to measure the effectiveness of the learning algorithm.

$$E = Err^2 \cong (X_t - h_W(x))^2 \quad (7)$$

Here

$X_t = h_W(x)$ (8)

hw (x) is the output of the perceptron.

The structured methodology adopted in the study is shown below:

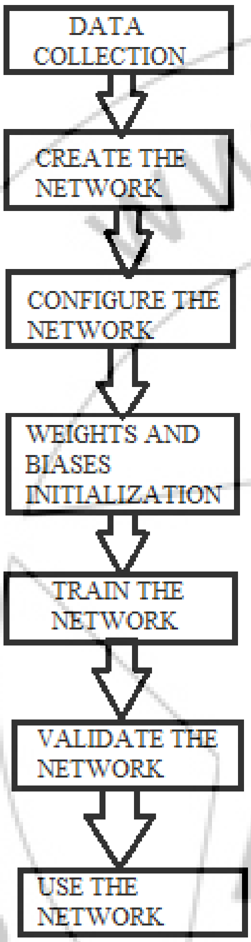

Figure 6: The structural methodology

- Collect data:
  First of all the essential data are collected and then the data set is prepared.
- Create the network:
  Secondly, using different ANN tools network is created.
- Configure the network:
  Then the configuration of the network is done i.e. three alternative networks are created.
- Initialize the weights and biases:
  Weights and biases are initialized for the networks.
- Train the network:

Training of the 70 % of the data is done.

- Validate the network:
  Validation of the network with the remaining 30 % of the data is done.
- Use the network:
  The network having RMSE value near to 1 is selected and the network is used for the prediction of future values.

4. Result and Analysis

The trend analysis of the water level variations for 16 years data is shown in Figure 7.

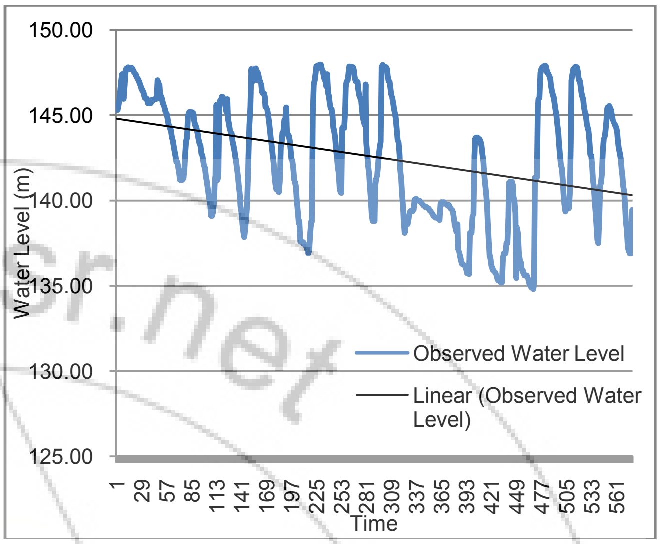

Figure 7: Variation in water level for Training Data set

The forecast accuracy of models using ANN Tools was evaluated by calculating the following statistic performance indicators: Root Mean Square Error (RMSE), Correlation Coefficient (R), Coefficient of determination (R^2) and Discrepancy Ratio (D) described in Table 1.

Table 1: Evaluation parameters of Trained Data

	RMSE	R	R^2	D
Feed Forward Distributed Time Delay	0.84	0.97	0.95	1.00
Layer Recurent	0.74	0.98	0.96	1.00
NARX	0.75	0.98	0.96	1.00

After observing the evaluation parameters, it is observed that Feed Forward Distributed Time Delay gives the best output having RMSE = 0.84, Correlation Coefficient, R = 0.97, Coefficient of Determination, R^2 = 0.95 and Discrepancy Ratio, D = 1.00.

The network diagram of Feed Forward Distributed Time delay is shown in Figure 8.

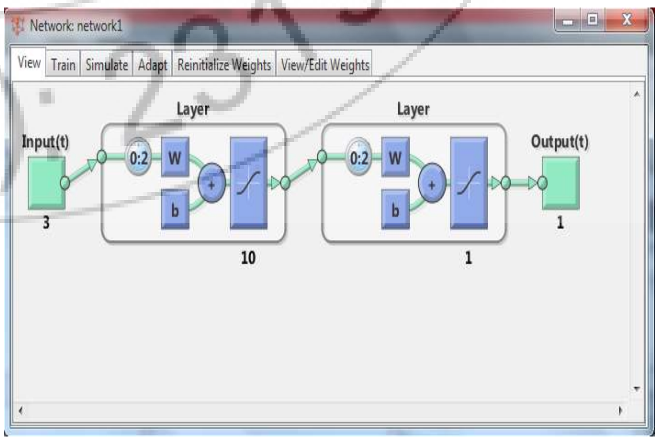

Figure 8: Network of Feedforward distributed time delay

The validation performance of feed forward distributed time delay is shown in Figure 9.

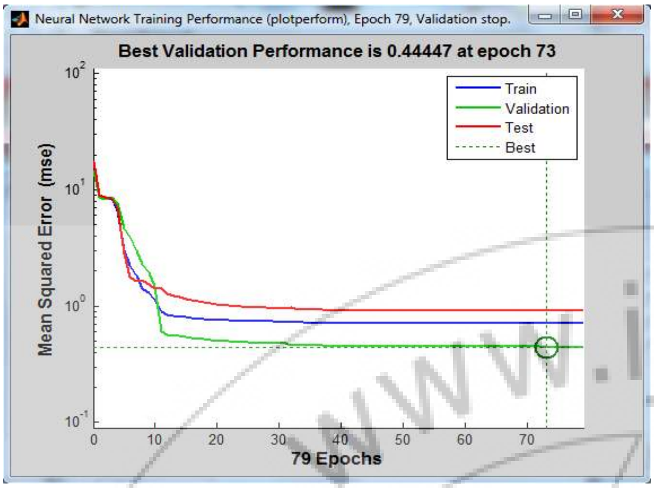

Figure 9: Validation performance of Feedforward distributed time delay for training data set

Figure 10 shows the Observed Water levels and predicted water levels.

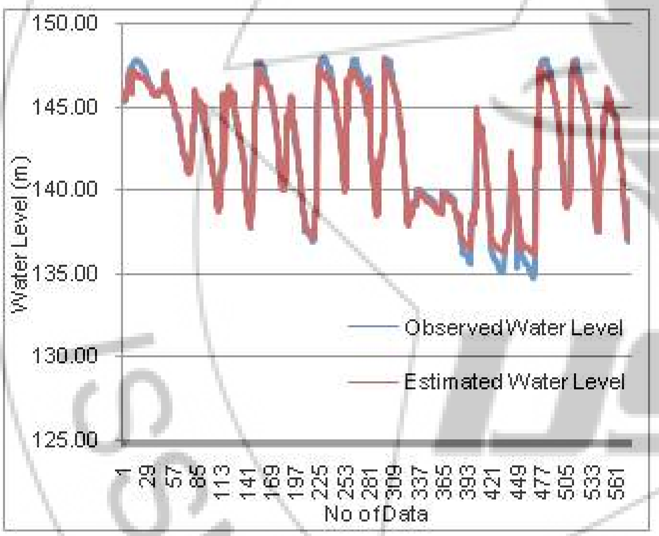

Figure 10: Observed and predicted Water Level for Training data using feedforward distributed time delay

Figure 11 Shows the scatter plot between observed and predicted water level for training stage.

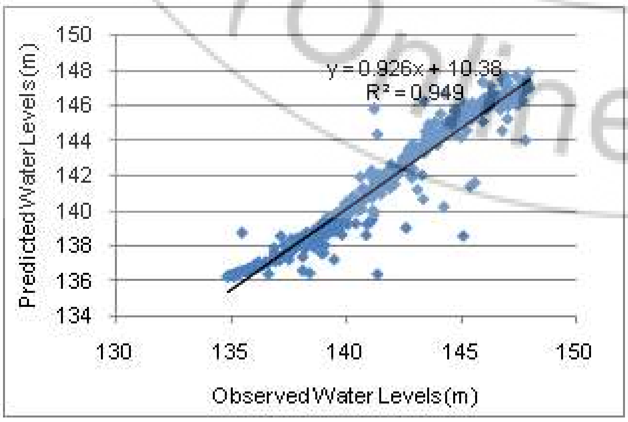

Figure 11: Observed and Predicted Water levels scatter plot for training data using Feedforward distributed time delay

The trend analysis of the water level variations from the year June 2006 to October 2013 i.e total of 07 years data is shown in Figure 12.

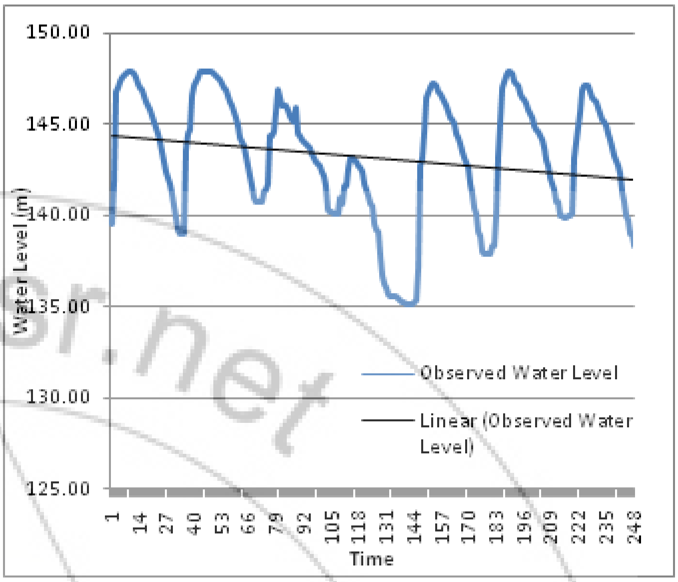

Figure 12: Variation of Observed Water Level for Validation data set

The forecast accuracy is validated on the remaining 30% of the data by evaluating the following statistic performance indicators: Root Mean Square Error (RMSE), Correlation Coefficient (R), Coefficient of determination (R^2) and Discrepancy Ratio (D) described in Table II.

Table 2: Evaluation parameters of Validated Data

	RMSE	*R*	*R^2*	*D*
Feed Forward Distributed Time Delay	0.90	0.97	0.94	1.00
Layer Recurent	0.71	0.98	0.96	1.00
NARX	0.87	0.97	0,94	1.00

Figure 13 shows the Observed and predicted Water levels using Feed Forward Distributed Time Delay.

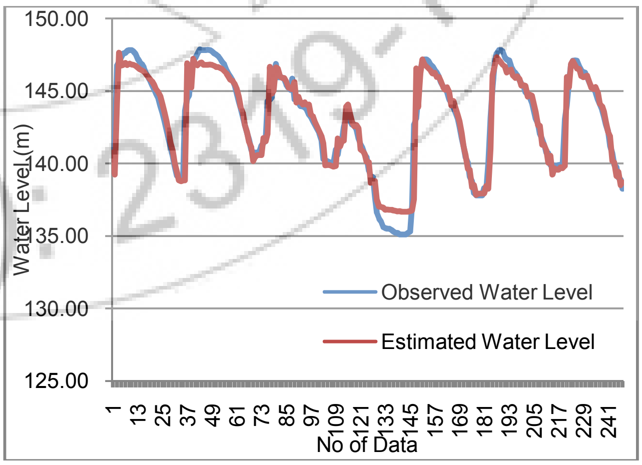

Figure 13: Observed and predicted Water Level for validation data using Feedforward distributed time delay

From the Validation results of ANN models, forecasted Water Level was plotted against the observed data to determine the relationship of these two variables (Figure14).

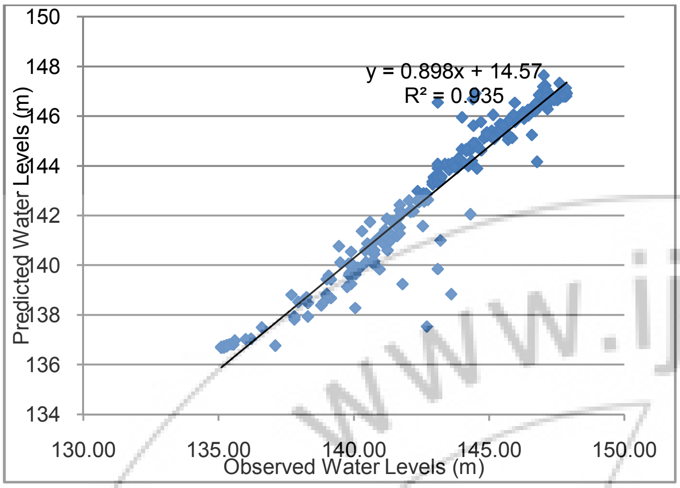

Figure 14: Observed and Predicted Water levels scatter plot for validation data using Feedforward distributed time delay

5. Conclusion

In this study, an Artificial Neural Network model has been developed to run real time Water Level forecast for Sukhi Reservoir, with lead time of 10 days. The 16 years data were used to train ANN models and 07 years data were used for validation. Three alternative models were tested to identify the appropriate model design to overcome the difficulty of predicting Water Levels.

Overall, the study indicates that the use of ANN model for Water Level forecasting may allow an extension of the lead-time above 10 days, whereby a reliable flood forecast which provides a quick prediction based on the past values may be issued. Feed Forward Distributed Time Delay gives the best output having RMSE , Correlation Coefficient, R, Coefficient of Determination, $R^2$and Discrepancy Ratio, D 0.84, 0.97, 0.95, 1.00 respectively in comparison of Layer recurrent which gives the output having RMSE 0.74, Correlation Coefficient, R 0.98, Coefficient of Determination, R^2 0.96 and Discrepancy Ratio, D 1.00 and NARX which gives the output having RMSE 0.75, Correlation Coefficient, R 0.98, Coefficient of Determination, R^2 0.96 and Discrepancy Ratio, D 1.00. Based on these results, among the three algorithms applied it can be concluded that ANN using Feed Forward distributed time delay is an appropriate predictor for real-time Water Level forecasting of Sukhi Reservoir Project.

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