Forecasting Reservoir Water Level of Kadana Dam Using Adaptive Neuro Fuzzy Inference System

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Abstract- Reservoir is very important hydraulic structure to store water in the dam. Reservoir is one of the structural approaches for flood protection and water storage. Reservoir water level mainly depends on the rainfall, inflow and outflow. Rainfall mainly influences the reservoir water level and inflow. The objective of this research work is to forecast the KADANA reservoir water level of Mahi River in Gujarat, using Artificial Intelligence method called Adaptive Neuro Fuzzy Inference System (ANFIS). In this work, two models were developed for two different inputs and for two different ANFIS Techniques called ANFIS-Grid Partitioning (ANFIS-GP) and ANFIS-Subtractive Clustering (ANFIS-SC). In Model 1 the Precipitation data from six upstream gauging stations of KADANA and a day's water level and output as a next day water level using the ANFIS Subtractive clustering technique. In Model 2, the Inflow of KADANA reservoir and a day's water level and output as a next day water level using the ANFIS Grid Partitioning Technique. To get an effective evaluation of the ANFIS model, these models were compared with another Artificial Intelligence method called Artificial Neural Network (ANN) and also compared with Actual Data. These model efficiency and accuracy were measured based on Root Mean square error (RMSE) correlation coefficient (R) and Co efficient of Determination (R^2). The results revealed that the ANFIS-GP and ANFIS-SC application could be applied effectively to forecast reservoir water level and the ANFIS-GP model has some extent better performance than the ANFIS-SC model in reservoir water level forecast.

Index Terms- KADANA, Reservoir forecasting Model, Adaptive Neuro Fuzzy Inference System, ANFIS-GP, ANFIS-SC, ANN.

I. INTRODUCTION

Reservoirs are the major component of water resource management, providing effective multi-purpose water storage for irrigation, water supply, hydropower, etc. which has to be designed and controlled at the optimal level. It can also serve as a protection during flood and drought situations. Information regarding reservoir water level is essential in the analysis and design of water resource project such as construction of dam, irrigation requirement and flood defense .Reservoir water level mainly depends on the rainfall, inflow and outflow. Rainfall mainly influences the reservoir water level and inflow. So the forecasting of the reservoir level is very useful for the flood management.

Recently Many Artificial intelligence methods and their combination with different strengths and weakness have combined for modeling in different aspect of water resources and other environment. Here, Adaptive Network Based Fuzzy Inferences System approach engaged in this study. The adaptive neuro fuzzy inference system is an Artificial Intelligence method which combines the feature of both Artificial Neural Network and fuzzy inference system. ANN has the ability of self learning and self adapting of data for forecasting but it is tough to know the learning process of it. However the fuzzy logic models are easy to implements a nonlinear mapping which is trained by a number of fuzzy IF THEN rules to define the local performance of mapping. The fuzzy membership parameters are optimized either by using a back-propagation algorithm or by a combination of both back propagation and least square method and their efficiency depends on the estimated parameters. ANFIS model was first used correspondingly by Takagi and Sugeno in 1985. ANFIS used for many field such as automatic control, decision analysis, expert system, data classification and forecasting-planning of the water resources.

II. RELATED WORKS

Chang and Chang (2006) present neuro fuzzy approach namely adaptive neuro fuzzy inference system (ANFIS) in forecasting 1 to 3 hours ahead water level of a reservoir for Shihmen reservoir. In their study, two ANFIS models were developed. The Model 1 with upstream flow pattern and current reservoir outflow as input variables and Model 2 with only upstream flow patterns. The result showed that the application of ANFIS could be used effectively to forecast reservoir water level for next three hours. Mehta and Jain (2008) develop an operation policy for Ramganga reservoir. ANFIS-GP and Cluster and Fuzzy Mamdani were used to calculate the release from all the developed models. The result indicated that the ANFIS-cluster provided the best performance with minimum error matched to Fuzzy Mamdani, but Fuzzy Mamdani was more users friendly. Shafie et al. (2007) developed an ANFIS model to forecast the inflow for the Nile River at Aswan High Dam in Egypt. The results showed that the ANFIS model. Guldal and tongal (2009) aimed to predict lake level considering hydro meteorological changes that take place in the Lake. For

that Recurrent Neural Network (RNN) and Adaptive Neuro Fuzzy Inference System (ANFIS) used as prediction models also the classical stochastic models such as Auto Regressive (AR) and Auto Regressive Moving Average (ARMA) models are generated and compared with RNN and ANFIS models. The results interpret that the RNN and ANFIS can be applied successfully and provide high accuracy and reliability for lake level changes than the AR and the ARMA models. Shafie et al. (2011) forecast the daily water level of Klang Gate dam, Malaysia using adaptive neuro fuzzy interface system (ANFIS) models for zero to 4 day time delays. The first model uses one daily rainfall at time (t) to time (t-4) as input and Second model uses daily rainfall and type of earlier water level of reservoir at time (t) to time (t-7). The model R (t-i) L (t-j), when i and j were the same, from zero to two days interval gives worthy result. Unes et.al (2017) examines the capability of Adaptive Neuro Fuzzy Inference System model to forecast daily reservoir volumes of Yarseli Dam. The reservoir volume differences were evaluated using average monthly precipitation, monthly total volume of evaporation, dam discharge volume, and released irrigation water amount. ANFIS results are equated with conventional multi linear regression (MLR) model. The result shows that reservoir volume was effectively assessed using ANFIS model than the conventional MLR model.

III. NEURO-FUZZY MODEL

Neuro fuzzy modeling discusses to the way of relating various learning techniques developed in the neural network to fuzzy modeling or to a fuzzy inference system (FIS). The basic structure of a FIS consists of three conceptual components like a rule base which has a selection of fuzzy rules, a database which defines the membership functions (MF) used in the fuzzy rules and a reasoning mechanism which performs the inference technique upon the rules to derive an output as shown in Fig. 1. FIS implements a nonlinear mapping from its input space to the output space. This mapping is accomplished by a number of fuzzy if then rules and each of which defines the local behavior of the mapping. The parameters of if then rule referred to as antecedents or premises in fuzzy modeling define a fuzzy region of the input space and the output parameters also consequents in fuzzy modeling specify the corresponding output. Hence the efficiency of the FIS depends on the estimated parameters. However the selection of the shape of the fuzzy set described by the antecedents corresponding to an input is not directed by any procedure. But the practice structure of a FIS makes it possible to integrate human knowledge about the system being modeled directly into the modeling process to choose on the important inputs, number of Membership Functions for each input etc. and the corresponding numerical data for parameter estimation.



Fig. 1 Fuzzy Inference System

IV. ANFIS Architecture

The ANFIS architecture contains fuzzification layer, inference process, defuzzification layer and summation as final output layer. Typical architecture of ANFIS is shown by figure 2. The process starts from layer 1 to layer 5. It is started by giving a number of sets of crisp values as input to be fuzzyfied in layer 1 passing through inference process in layer 2 and layer 3 where rules applied calculating output for each equivalent rules in layer 4 and in layer 5 all output from layer 4 are summed up to get one final output. The main purpose of the ANFIS is to determine the optimal values of the corresponding fuzzy inference system parameters by applying a learning algorithm using input output data sets. The parameter optimization is done in such a way throughout training that error among target and actual output is reduced. Parameter is optimized by hybrid algorithm which is combination of least square estimate and gradient descent method. The parameter to be optimized in ANFIS is the premise parameters which describe the shape of membership function and consequent parameter describe the overall output. The optimum parameter found is then used in testing to determine the reservoir water level.



Fig. 2 Architecture of ANFIS

V. STUDY AREA AND DATA

The Kadana dam of Mahi River in Gujarat is chosen as the study area for present work. The Mahi River moves over state of Gujarat, Madhya Pradesh and Rajasthan of total area $34,842 \text{ Km}^2$ of a span 330 km and width 250 km. The right tributary of Mahi is Som and Left tributary of Mahi River are Anas and Panam. Kadana Dam of Mahi River is located in valley of low range of in Dahod, Gujarat which has boundary with Rajasthan. The area of catchment of this scheme is $25,520 \text{ Km}^2$. The Dam is compound of Earth and masonry Gravity construction increasing 58m overhead to branches with top length of dam 1551m with main spillway of 406m and 113 m long additional spillway in right bank of river. The effective storage capacity of reservoir is 1203Mm3. The Advantage of this scheme is Irrigation, Hydro power and Flood Protection. The Fig 3 shows location of KADANA dam in Indian Map. The Precipitation data of six upstream gauging station of Kadana namely as Anas, Paderdibadi, Dhariawad, Chakliya, Mataji , Rangeli and the water level and Inflow of Kadana dam for Monsoon period of year 2002 to 2009 of total 976 data were used in this study.



VI. MODEL DEVELOPMENT

There are no fixed Rules for development an ANFIS model even though a general framework can be followed Based on past successful presentations in engineering. The selection of proper input and output data possess the prime importance and needs to be selected carefully. To Forecast Reservoir water level for Kadana using Adaptive Neuro Fuzzy Inference System here two different models for two different ANFIS technique called Grid Partitioning and Subtractive clustering were used. Model 1 uses the Precipitation data from six upstream gauging station of Kadana namely as Anas, Paderdibadi, Dhariawad, Chakliya, Mataji , Rangeli and also use the water level data as input at a time (t-1) to forecast reservoir water level at time (t) using the ANFIS Subtractive clustering technique. Here the four numbers of Gaussian Membership Function with 0.2 Range of Influence and Hybrid optimization method for 200 epochs was used. In Model 2, the Inflow of Kadana reservoir and water

level at time (t-1) were used as input to forecast reservoir water level at time (t) using ANFIS Grid Partitioning Technique. Here the three number of Gaussian Membership Function with Linear Transfer function of output layer and Hybrid optimization method for 200 epochs was used. This ANFIS model performance was compared with other Artificial Intelligence technique called Artificial Neural Network (ANN) and with the observed water level. In this work statistical measures like correlation coefficient, coefficient of determination and root mean square error were used for evaluating the performance of developed models.

Root Mean Squared Error (RMSE)

The root mean square error measures the forecasted accuracy of the established model. It calculates difference between forecasted and actual values. The perfect fit model has zero RMSE and increased value of RMSE show higher deviation between forecasted and actual values. It is calculated using following equation (1),

$$\mathbf{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (X_i - Y_i)^2}$$
(1)

Where, Xi = N no of Actual output and Yi = N no of Forecasted output

Co efficient of Correlation (R)

The coefficient of correlation measure the strength of linear relationship of developed model. The correlation coefficient shows the quantity of closeness between actual and forecasted values. The values of R close to 1 represent good model performance and 0 represents poor model performance. It is calculated using the following equation (2).

$$\mathbf{R} = \frac{\sum_{i=1}^{N} (X - X_{mean}) (Y - Y_{mean})}{\sqrt{\sum_{i=1}^{N} (X - X_{mean})^2 \sum_{i=1}^{N} (Y - Y_{mean})^2}}$$

Where, X = Actual output, $X_{mean} = Mean of Actual output$, Y = Forecasted output, $Y_{mean} = Mean of Forecasted output$

Co efficient of Determination (R²)

The coefficient of determination is a main output of regression analysis. It is taken as the proportion of the variance in the dependent variable that is predictable from the independent variable. The coefficient of determination is the square of the correlation value between predicted y scores and actual y scores which ranges from 0 to 1. The coefficient of determination value 0 means that the dependent variable cannot be predicted from the independent variable and coefficient of determination value 1 means the dependent variable can be predicted without error from the independent variable. It is calculated using the following equation (3).

$$R^{2} = \frac{\left[\sum_{i=1}^{N} (X - X_{\text{mean}})(Y - Y_{\text{mean}})\right]^{2}}{\sum_{i=1}^{N} (X - X_{\text{mean}})^{2} \sum_{i=1}^{N} (Y - Y_{\text{mean}})^{2}}$$
(3)

Where, X = Actual output, $X_{mean} = Mean of Actual output$, Y = Forecasted output, $Y_{mean} = Mean of Forecasted output$

VII. RESULT AND ANALYSIS

The data are divided into 80% for training and 20% for testing. The result obtained from ANFIS model 1 and model 2 is shown below in table 1. From the table 1 it is shown that Both the model, Model 1 and model 2 gives reliable result, but the Model 2 having Inflow and Water level as input to forecast reservoir water level gives Accurate and comparatively more reliable result than Model 1 which has Precipitation data from upstream six gauging station and water level as input to forecast reservoir water level.

| Table 1 Performance evaluation of model on training and testing period for AINFIS model | | | | | | | |
|---|--------------|----------------|----------|----------|----------|----------------|--|
| MODEL 1 : PRECIPITATION+WATER LEVEL | | | | | | | |
| TECHNIQUE | NO. OF MF | NO.OF INPUT | PHASE | RMSE | R | R ² | |
| SUBSTRACTIVE | 4 | 7 | TRAINING | 0.005614 | 0.999480 | 0.999 | |

| CLUSTERING | | | TESTING | 0.009936 | 0.988757 | 0.9776 | |
|------------------------------|--------------|----------------|----------|----------|----------|----------------|--|
| MODEL 2 : INFLOW+WATER LEVEL | | | | | | | |
| TECHNIQUE | NO. OF MF | NO.OF INPUT | PHASE | RMSE | R | R ² | |
| GRID PARTITIONING | 3 | 2 | TRAINING | 0.000063 | 0.999999 | 1 | |
| | | | TESTING | 0.000619 | 0.999956 | 0.9999 | |

COMPARISION OF FORECAST DATA WITH ACTUAL DATA



Fig.4 Scatter plot for Actual and Forecasted Water level for Training of Model 1



Fig.5 Scatter plot for Actual and Forecasted Water level for Testing of Model 1



Fig.6 Scatter plot for Actual and Forecasted Water level for Training of Model 2



Fig.7 Scatter plot for Actual and Forecasted Water level for Testing of Model 2

ANN MODEL ANAYLYSIS

For the same Two Model, ANN Analysis is done for forecasting reservoir water level of KADANA dam. Here for both models 'Levenberg-Marquardt' Algorithm was used as learning algorithm with Transfer function sigmoid in hidden layer and Linear in output layer and only the hidden neuron was changed and best ANN architecture was selected based on high regression value and low mean square error.

| MODEL 1 : PRECIPITATION+WATER LEVEL | | | | | | | |
|-------------------------------------|-----------|----------|----------|----------|----------------|--|--|
| MODEL ARCHITECTURE | ALGORITHM | PHASE | RMSE | R | R ² | | |
| 7-2-1 | LM | TRAINING | 0.004935 | 0.999633 | 0.9993 | | |
| | | TESTING | 0.002701 | 0.999242 | 0.9985 | | |
| MODEL 2 : INFLOW+WATER LEVEL | | | | | | | |
| MODEL ARCHITECTURE | ALGORITHM | PHASE | RMSE | R | R ² | | |
| 2-4-1 | LM | TRAINING | 0.004344 | 0.999691 | 0.9994 | | |
| | | TESTING | 0.002943 | 0.999508 | 0.999 | | |

Table 2 Performance evaluation of model on training and testing period for ANN model

From the table 2 it is clear that Model 2 having Inflow and Water level as input to forecast reservoir water level gives comparatively more reliable and accurate result than Model 1 which has Precipitation data from upstream six gauging station and water level as input to forecast reservoir water level.

COMPARESION BETWEEN ANFIS AND ANN MODEL

The First model of Reservoir water level forecasting has input as precipitation from six up steam gauging station of Kadana and water level hence it has 7 inputs so to find reservoir water level ANFIS uses the subtractive clustering technique as there was inputs more than five it gives slightly less accuracy compare to ANN first model. The First model of ANFIS has coefficient of correlation value and corresponding RMSE (root mean square error) of testing is 0.988757 and 0.009936, while ANN has coefficient of correlation value and corresponding RMSE value of testing is 0.999242 and 0.002701. The Second Model of Reservoir water level forecasting has input as Direct Inflow and water level hence it has 2 inputs so to find reservoir water level ANFIS uses the Grid partitioning Technique, which gives Accurate and perfect result for training by coefficient of correlation value and corresponding RMSE value as 0.9999 and 0.000063, for testing it's coefficient of correlation value and corresponding RMSE value as 0.9999 and 0.000063, for testing it's coefficient of correlation value and testing as it's training coefficient of correlation value and corresponding RMSE value is 0.9999 and 0.000619, While ANN model gives a comparatively little less result for both training and testing as it's training coefficient of correlation value and corresponding RMSE value is 0.999691 and 0.004344, and it's coefficient of correlation value and corresponding RMSE value and corresponding RMSE value is 0.999631.

From the above result it is clear that both the ANFIS and ANN model were able to Forecast Reservoir water level with adequate accuracy. For the Model1, which has more than six input ANN Technique provides comparatively Better result than ANFIS model which needs to adopt subtractive clustering, while there is less than six input like model2, Grid partitioning technique of ANFIS performed as Perfect model than ANN with coefficient of correlation value and corresponding coefficient of determination value as 0.9999 and 1 for the same input.

VIII. CONCLUSION

The Adaptive Neuro Fuzzy Inference System (ANFIS) model was developed in this study to forecast Reservoir water level of Kadana of Mahi River in Panchmahal. Two types of ANFIS Model of two different inputs and two different ANFIS techniques called Grid Partitioning and Subtractive clustering was used to forecast the reservoir water level. The Model 1 which has input of Precipitation data from six upstream gauging station of Kadana namely as Anas, Paderdibadi, Dhariawad,

Chakliya, Mataji , Rangeli and also the water level data at a time (t-1) to forecast reservoir water level at time (t) using the ANFIS-SC. In Model 2, the Inflow of Kadana reservoir and water level at time (t-1) were used as input to forecast reservoir water level at time (t) using ANFIS-GP. The forecasted model result was compared with ANN model and also compare with the Actual data. The model assessment was made by employing various statistical indices viz. Root mean square error (RMSE), correlation coefficient (R) and Co efficient of Determination (R^2). The following conclusions were drawn from the results of this study:

- From the result of Statistical value of Coefficient of correlation, Root mean square error and Coefficient of Determination of ANFIS-SC corresponding value are 0.9887, 0.0099 and 0.9776 and for ANFIS-GP corresponding value are 0.9999, 0.0006 and 0.9999 which indicate that both ANFIS Technique ANFIS-SC and ANFIS-GP gives reliable result and can be applied successfully to forecast reservoir water level considering any model input.
- It also interpret that ANFIS-GP model using Inflow and Water level as input data gives accurate and almost perfect result compare to ANFIS-SC model using Precipitation data from six upstream gauging station and Water level as input for this study.
- By comparing another Artificial Intelligence method called ANN with the result of ANFIS model, ANN model has Statistical value of Coefficient of correlation, Root mean square error and Coefficient of Determination for Model 1 having Architecture 7-2-1 has corresponding value 0.9992, 0.0027 and 0.9985 and for Model 2 having Architecture 2-4-1 has corresponding value 0.9995, 0.0029 and 0.999 which indicate that ANN model also gives reliable result and it also interpret that It also interpret that Model 2 using Inflow and Water level as input data gives accurate result compare to Model 1 using Precipitation data from six upstream gauging station and Water level as input for this study.
- During Execution of both ANFIS and ANN model it was observed that ANFIS model execution time was less compared to ANN model.
- The limitation in ANFIS model using ANFIS-GP is "Curse of Dimensionality" means that ANFIS-GP produce rules by computing all possible combination of Membership Function of all input. The number of fuzzy rules in ANFIS-GP increases exponentially with the increasing number of input variable which leads to increase of Recreation time and Reduced the result of high dimensional problem hence to overcome this we had use ANFIS-SC Technique in Model 1 having seven input which has advantage to find optimum rule that the Resultant rules in ANFIS-SC are more Tailored than ANFIS-GP. This reduces the problem of selection of larger number input without regard to their explosion of rules when input data has a high Dimension

IX. REFERENCES

- [1] Suriyati Abdul Mokhtar, H. (2016). Modeling reservoir Water Release Decision using Adaptive Neuro Fuzzy Inference System. Journal of ICT, 141-152.
- [2] Fatih Unes, F. G. (2017). Prediction of Dam Reservoir Volume Fluctuations Using Adaptive Neuro Fuzzy Approach. European Journal of Engineering and Natural sciences, 144-148.
- [3] Fi-john Chang, Y.-T. C. (2006). Adaptive neuro-fuzzy inference system for prediction of water level in reservoir. Journal of science direct, Elsevier, 1-10.
- [4] Gungor, M. F. (2009). Monthly total sediment forecasting using adaptive neuro fuzzy inference system. Springer-Verlag, 259-270.
- [5] Mansour Talebizadeh , A. M. (2010). Uncertainty analysis for the forecast of lake level fluctuations using ensembles using ANN and ANFIS model. ScienceDirect Elsevier, 4126-4135.
- [6] N. Valizadeh1, A. E.-S.-S. (2011). Daily water level forecasting using adaptive neuro-fuzzy interface system with different scenarios: Klang Gate, Malaysia. Internatioal journal of physical science.
- [7] Nariman Valizadeh, A. E.-S. (2013). Forecasting the Level of Reservoirs Using Multiple Input. Springer Science, 3319-3331.
- [8] Rama Mehta, S. K. (2008). Optimal Operation of a Multi-Purpose Reservoir. Springer Science, 509-529.
- [9] Taha, A. E.-S. (2006). A neuro-fuzzy model for inflow forecasting of the Nile. Springer Science, 533-556.
- [10] Tongal, V. G. (2009). Comparison of Recurrent Neural Network Adaptive Neuro fuzzy inference system and stochastoc models in egirdir lake level forecasting. Springer Science, 105–128.
- [11] Jang, J.-S. R. (1993). ANFIS: Adaptive Network based Fuzzy Inference System. IEEE Transactions on Systems Man and Cybernetics, 665-685.
- [12] Hydrology, A. T. (2000a). Artificial neural networks in Hydrology, I:Priliminary Concepts. J. Hydrol. Engng ASCE, 115-123.
- [13]Hydrology, A. T. (2000b). Artificial neural networks in Hydrology, II:Hydrologic Application. J. Hydrol. Engng ASCE, 124– 137.
- [14] Jyh-shing Jang roger, C.-T. s. (1997). Neuro-fuzzy and Soft Computing. Prentice-Hall, Upper Saddle River, New.