Forecasting Reservoir Water Level Using Adaptive Neuro Fuzzy Inference System - A Review

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.***Abstract***- Reservoir is a physical structure such as pond or lake naturally or artificially developed to store and regulates the water. Reservoir dam is one of the defense appliance for both flood and drought calamities. The reservoir water level forecasting has been significant in the reservoir management and water resources. For many years, reservoir water level approximation was based on operator's experience, mathematical model and curves. In recent times Artificial intelligence methods such as Adaptive Neuro Fuzzy Inference System (ANFIS) are used in many hydrological characteristics such as forecasting and classification parameters. The advantage of ANFIS methods is that they can manage dynamic, non-linear and noisy data, especially when the fundamental physical relations are very complex and not fully understood. These methods also provide fast, consistent and low-cost solutions. This is a literature review based paper aims at studying various researches already done in the field of ANFIS in reservoir water level forecasting.

Index Terms- **Reservoir level, forecasting, Adaptive Neuro Fuzzy Inference System**

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 dam construction, irrigation needs and flood control. The parameter that influence reservoir water level are amount of rainfall, water release, evaporation, soil moisture and infiltration that represents uncertainties and it is very essential to consider in water resource operation.

The inflow quantity strictly depends on cross section area of river, bed slope, type of soil and soil characteristics, vegetation area and its characteristics in proximity environmental and rainfall characteristics, groundwater-table situation and aspects, etc. The water level of reservoir is depending on to the inflow of reservoir. Hence, for any reservoir operation and safety procedure, the timely water level as well as management and modification of water level during the high-flood time has demanded major attention to avoid any disaster or calamity in the downstream region which tends to importance of water level forecasting, as timely forecasting of water level sometimes save people from disasters or calamity.

Here, Adaptive Network-Based- Fuzzy Inferences System (ANFIS) approach engaged in this study. The adaptive neuro-fuzzy inference system (ANFIS) is a soft computing method which combines the feature of both Artificial Neural Network (ANN) and fuzzy inference system (FIS). ANN has the capability of self-learning and self-adapting of data for forecasting but it is difficult 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 symmetrically by (Takagi and Sugeno, 1985). ANFIS used for many field such as automatic control, decision analysis, expert system, data classification and forecasting-planning of the water resources.

II. 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: 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 (see 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, each of which defines the local behavior of the mapping. The parameters of the if-then rules (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 MFs for each input, etc. and the corresponding numerical data for parameter estimation.

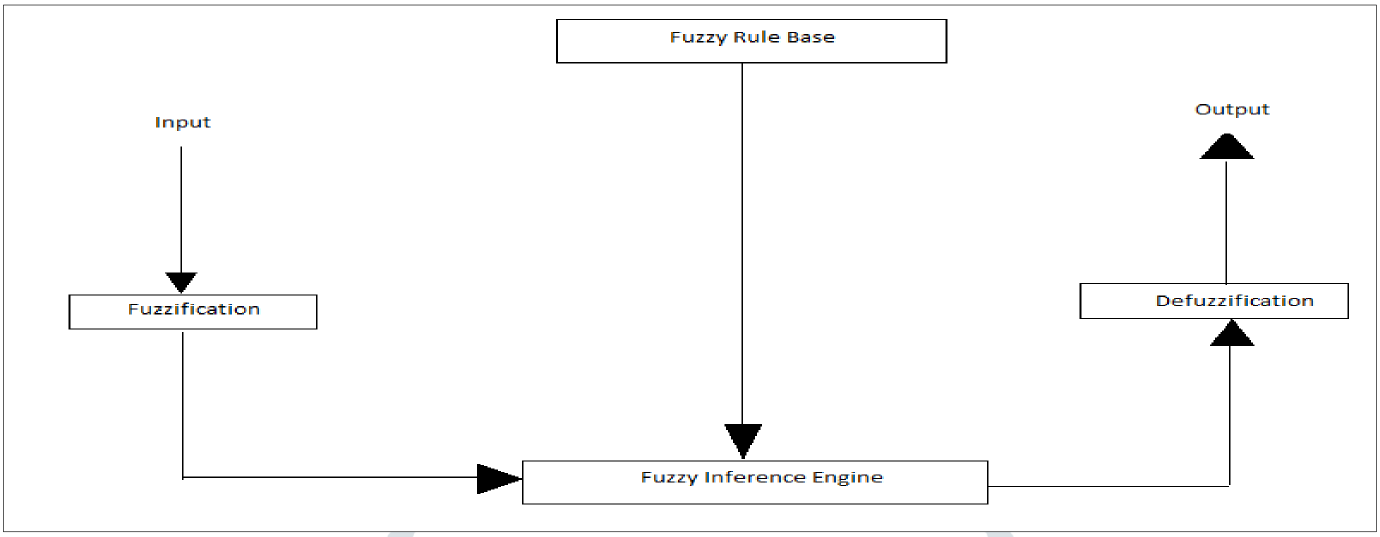

Fig. 1 Fuzzy Inference System

III. 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 prediction

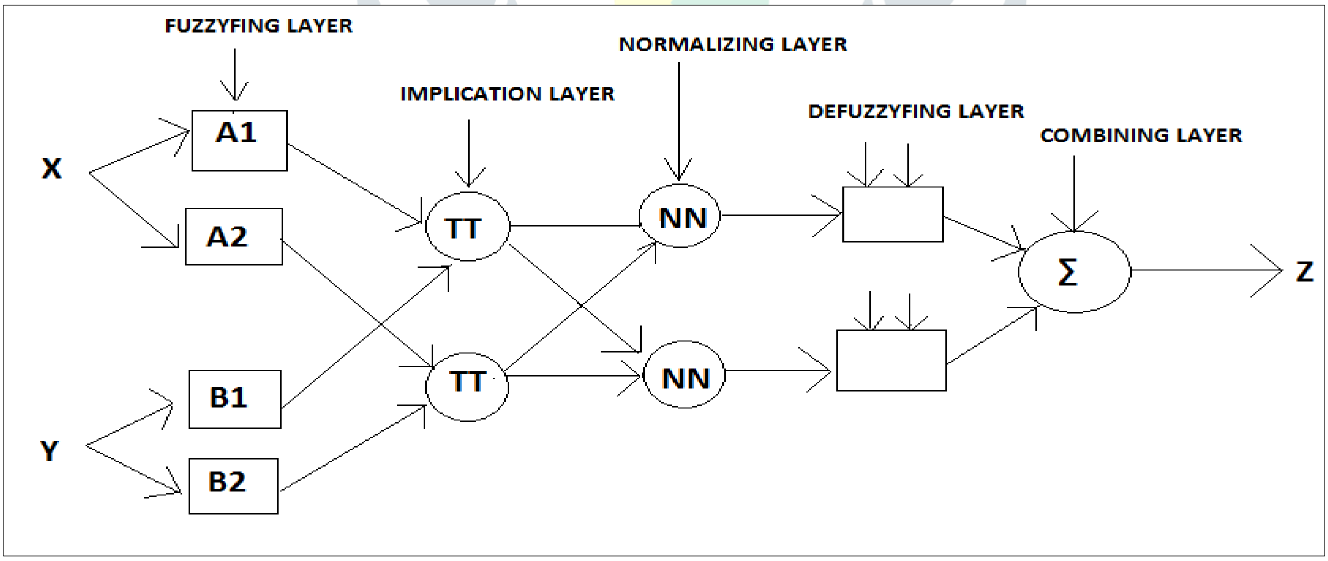

Fig. 2 Architecture of ANFIS

IV. LITERATURE REVIEW

Forecasting reservoir water levels using ANFIS have been carried out by different researchers.

Chang and Chang (2006) presents neuro-fuzzy approach namely adaptive neuro-fuzzy inference system (ANFIS) in forecasting 1–3 hours-ahead water level of a reservoir during flood periods for Shihmen reservoir, Taiwan. A large number of storm and heavy rainfall events with 8640 hourly data sets collected in previous 31 years were used. In their study, two

ANFIS models were developed: Model 1 with upstream flow pattern and current reservoir outflow as input variables; Model 2 with only upstream flow patterns (without reservoir outflow as input variables). Performances of model verified by Root mean square error, correlation coefficients and mean absolute error. The result showed that the application of ANFIS could be used effectively to forecast reservoir water level for next three hours. Furthermore, the model with upstream flow pattern and current reservoir outflow as input variables has constantly superior performance with regard to indexes than the model without this input.

Shafie et al. (2007) developed an adaptive neuro-fuzzy inference system (ANFIS) model to forecast the inflow for the Nile River at Aswan High Dam (AHD) in Egypt on monthly basis. A past database of monthly inflows at AHD recorded over the past 130 years was used to train the ANFIS model and to test its performance. Data samples comprised daily water level of reservoirs in 4 years (2007-2011) for any model. The inflow estimating model was designed for each month resulting into 12 ANFIS models. The performance of the ANFIS model was compared to ANN model. Three statistical measures were used to test the goodness to fit of the ANFIS model include Forecasting error, Maximum Relative error and Correlation coefficient. The results proved that the ANFIS model was capable of providing higher inflow predicting accuracy mainly at extreme inflow events compared with that of the ANN model.

Mehta and Jain (2008) develop an operation policy for Ramganga reservoir behind Ramganga dam, Kalagarh, India which was to be used for multi-purpose reservoir. Three Fuzzy Rule Based (FRB) models for monsoon period and three for non-monsoon period have been developed and tested. The data of Monthly reservoir level, inflow, demand & reservoir level for flood control for the 31 year period (from 1974 to 2004) were used. Twelve month-wise databases have been prepared for ANFIS- Grid with 111 manually generated rules and Mamdani FIS structure with 27 automatic generated rules. Models are established for monsoon (July to October) and non-monsoon (November to May) periods with fuzzy, ANFIS-Grid and ANFIS-Cluster techniques. ANFIS- Grid and Cluster and Fuzzy Mamdani were used to calculate the release from all the developed models. The performance criteria used are Root mean square error, Correlation coefficient and Model efficiency. 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.

Guldal and tongal (2009) aimed to predict forthcoming lake level of Egirdir in Turkey considering hydro meteorological changes and anthropogenic activities that take place in the Lake. For that Recurrent Neural Network (RNN) and Adaptive Neuro Fuzzy Inference System (ANFIS) used as prediction models which have various input structures and the best fit model was studied. Also the classical stochastic models, Auto-Regressive (AR) and Auto-Regressive Moving Average (ARMA) models are generated and compared with RNN and ANFIS models. The performances of the models are examined in the form of numerical and graphical comparisons in addition to some statistic efficiency criteria. The results indicated 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.

Firat et al. (2010) used Adaptive Neuro Fuzzy Inference System method to build monthly sediment forecasting system at the great Menders basin. The models with several input structures are made for the purpose of identification of the best structure. Different combinations of the antecedent values of monthly river flows are used for constructing the appropriate input structure. The performances of the input models in training and testing sets were compared with the observed data. To get more precise evolution of the results of ANFIS models, the best fit model architectures were tested by Artificial Neural Network and Multiple Linear Regression methods. The performance of ANFIS models for training and testing data sets were calculated using correlation coefficient, efficiency, and normalized root mean square error. The outcomes of the three methods were compared and it was checked that the ANFIS is superior and can be applied effectively to found monthly total sediment forecasting models.

Shafie et al. (2011) aimed to forecast the daily water level of Klang Gate dam, Malaysia using adaptive neuro fuzzy interface system (ANFIS).Various models from zero to 4 day time delays are considered in each kind of models. The daily data of average rainfall and water level of Klang Gate dam from the year 1997 to 2007 used. To find a superior ANFIS model, two different types of model in structure and type of inputs were used. The first set of model uses one daily rainfall at time (t) to time (t-4) as input in four different models. Second set of model uses daily rainfall and type of earlier water level of reservoir at time (t) to time (t-7) as inputs in seven different models. Five generalized bell-shaped membership function is used in one input modeling of first set and three generalized bell and Gaussian membership function are used in two input ANFIS model. Models performance tested in form of Root mean square error Mean absolute error, Correlation coefficient and Mean absolute percentage error. The model R (t-i) L (t-j), when i and j were the same, from zero to two days interval gives worthy result.

Talebizadeh, and Moridnejad (2011) in their study presents different ANN and ANFIS models to forecast the lake level fluctuations in Lake Urmia in northwest of Iran. The past data of average monthly inflow, evaporation, precipitation and lake level form the period of 1972–2000 were used to find the best input variables to the models. Three performance criteria including the correlation coefficient (R), root mean square error (RMSE), mean absolute error (MAE) were used. The results show that for 1 and 3 months-ahead of lake level forecasts, the ANFIS model does not have the limitation of ANN in estimating values that are outside of the range of data used for training the models. Hence, the results of the ANFIS model are superior to ANN ones in that they are equally more accurate and with less uncertainty.

Valizadeh and El-Shafie (2013) recommended multiple input fuzzifications in Adaptive Neuro Fuzzy Inference System to forecast the dam level of Klang Gates Dam in Malaysia. This study defined ANFIS structured model using three different time gaps were studied with two different MFs for the two inputs, rainfall and dam level from previous days of Klang Gates Dam in Malaysia. For this study, 4380 data observations of the daily rainfall and dam level were collected from 1997 to 2007. The present model was equated with the traditional ANFIS by fuzzifying each type of input in the modeling system to establish the behavior of the different membership functions for all input. Three different time lags were observed with two different membership functions (MF) that were the generalized bell-shaped MF and the Gaussian MF for the two inputs, rainfall and dam level from previous days. Based on statistical evaluations such as Root mean square error, correlation coefficient, Mean absolute percentage error and Mean absolute error shows that model employed different types of MFs executed better than the other models, especially for time lag.

Mokhtar et al. (2016) developed a reservoir water release decision model using Adaptive Neuro Fuzzy Inference System. In this study, the Timah Tasoh reservoir and rainfall from five upstream gauging stations were used as a case study. In this study, two ANFIS models were developed for gate opening decisions, Model 1 and Model 2. Model 1 contained of 23 input variables (temporal rainfall patterns from five upstream gauging stations and the current reservoir water level) and Model 2 contained of 22 input variables (temporal rainfall patterns from five upstream gauging stations without the current reservoir water level). The model was evaluated by Root mean square error and Mean absolute error. The result showed that the application of ANFIS could be used effectively for modeling reservoir water release decision. The Result showed that the first model with the extra input showed better performance with the lowest square error related to the second model.

Unes et.al (2017) examines the capability of Adaptive Neuro Fuzzy Inference System model to forecast daily reservoir volumes of Yarseli Dam in Turkey was selected for this study. The reservoir volume differences were assessed using average monthly precipitation, monthly total volume of evaporation, dam discharge volume, and released irrigation water amount. The data sample contains of 10 years of daily records of basin rainfall, volumes of inflow river water, evaporation from Reservoir, Dam Spillway Release, volume of Irrigation water and change Reservoir Volume. ANFIS outcomes are equated with conventional multi-linear regression (MLR) model. The Performance was measured in terms of mean square error (MSE) Mean absolute error (MAE) and coefficient of correlation (R) between estimated and observed volume. The result display that reservoir volume was effectively assessed using ANFIS model with low mean square error and high correlation coefficients. Hence, ANFIS offers improved estimations of the dam reservoir volume fluctuations than the conventional MLR model.

V. CONCLUSION

- During the literature review it was observed that different researcher's uses different parameters of input such as rainfall, inflow, water level, outflow, evaporation etc. for different time lags.
- Most of the researcher used ANFIS – Grid Technique and Hybrid learning algorithm which combined gradient descent method and the least-squares method.
- The performance of ANFIS models for training and testing data sets were checked by Root mean square error (RMSE), correlation coefficients (R) and mean absolute error (MAE).
- Artificial Neural Network (ANN), Multiple Linear Regression (MLR) Auto-Regressive (AR) and Auto-Regressive Moving Average (ARMA) and other model used to compare with ANFIS. The result indicated that ANFIS can be applied successfully and provide superior performance for forecasting reservoir water level.

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