Control on Hydropower Plant using Fuzzy Neural Network based on Right-Angle Triangle Membership

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Abstract— A new fuzzy control method for hydropower generation in the presence of input random variables is investigated in this paper. Firstly, they decomposed the annual input variables like the net head of the turbine, and flow rate of water into a certain number of detail signals through artificial neural network (ANN) transform. ANN model used to predict the annual power generation. After the stationary simulation prediction model is obtained, the prediction results were superposed. The superposed prediction results are corrected by using the more relaxed and simplified sufficient stability conditions are given as a new set of right-angle triangle membership function (RFANN), which have been guaranteed by strict mathematical derivation. Thirdly, the control method has good robustness, which could resist the random disturbances. Finally, simulation results have demonstrated the robustness and effectiveness of this new approach when compared with the existing one.

Index Terms— Small Hydropower Plant; Fuzzy Artificial Neural Network; Himreen Lake Dam; Right-Angle Triangle Membership Function;

I. Introduction

For generating power, hydroelectric power is the most widely used renewable sources of energy. Hydro power generation depends on the available flow and altitude from which it falls [1, 2]. The main components of soft computing are fuzzy logic (FL) and Artificial Neural Networks (ANNs) [3]. Artificial Neural Network and fuzzy logic control techniques can be used for modeling and control on the hydro generation scheduling extent at a certain point. These techniques are less subjected to the constraints of physical description and ability to map the logical input/output relations [2, 3]. the ANN model performs in some cases better than the physically-based models [4].

Several related works include two main techniques like ANN, FL using different case studies in hydro power generation to forecast stream flows using hybrid wavelet-neuro-fuzzy model [5], modeling daily discharge [3]. Prediction using neuro-fuzzy approach for Short-term water level [2], and long term [6]. An adaptive fuzzy fractional order proportional integral derivative (PID) control for pumped storage hydro [1, 7, 8], and automatic generation control of multi-area power system [9]. Hybrid neuro-fuzzy approach for automatic generation control [10], load frequency control [11]. Fuzzy rule-based model for hydropower reservoirs operation [12], optimal multi-objective [13]. Robust Takagi-Sugeno fuzzy control hydropower system for fractional order [14], modeling for three-phase [15], and predict speed [16, 17]. Rough fuzzy artificial neural network using for classification [18-20], Modeling of ANFIS [21, 22], and prediction [23, 24].

From a modeling viewpoint, a Hydropower operation is a unpredictable [15], complex [3] due to the stochasticity of hydrologic variables [12], non-linear system [14] due to uncertainty of the process [1], non-minimum phase system [14, 15], uncomfortable for managers and operators because of the complicated optimization techniques used in the models [12]. Nevertheless, PID controllers fail to cope with operational constraints. Thus, hydro plant operation needs an advanced control [16]. In addition, modeling hydropower systems, based on a power generation approach, usually requires a large number of input data, which are not readily available [2, 3]. Therefore, other models such as fuzzy rule-based models have been suggested to overcome these limitations [12]. Since the development of hydropower prototypes is costly, it is better to model by ANN coupled with FLC model [15, 25].

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The concept of Fuzzy logic coupled with an artificial neural network appears a promising technique for mapping the domain of hydropower operation as per the choice of the operation condition [26, 27]. The fuzzy control method is a classic control scheme. The nonlinear model is expressed by fuzzy IF-THEN rules, and the certain region of the system state is locally represented by the linearization description. However, the control quality is not very good. Besides, the oscillation occurs more frequently before the states become stable. And the conventional FL method has little ability to resist external disturbances [2, 14]. The FL doesn't have the capability of learning and it is memory less [19]. An element of a fuzzy set naturally belongs to the set of membership values from the interval [0, 1] [24].

An enhanced fuzzy neural network for optimal control is proposed, a new algorithm to realize the feature selection, with the intention to use the rough set as a tool for structuring the fuzzy artificial neural network (FANN) by automatically computing the proper membership thresholds instead of choosing them. In return, make output parameter values of the intermediate stations. moreover, because of the numerous parameters of ANN with FLC and the randomness always exists in the right-angle triangle membership function is also proposed to solve the optimized parameters selection problem.

II. Methodology

Hydropower Function

The hydro-turbine obtains mechanic hydropower and changes it to rotational power mechanically and it's coupled to an electric power generator. Actually, the turbine efficiency depends on the turbine's power, the turbine's type, fluid percentage, etc. Kaplan turbine may be observed that its efficiency is reaching to the maximum value for a various flow rate of water, proving these kinds of turbines can be desirable for a river with a variant in the regime of water flow rate. In general, the electrical power generators employed in small hydropower plant (SHP) are synchronous machines which generate electrical power by alternating current. Where, this synchronous machine has been strongly linked up with the turbine shaft to convert the mechanical rotational energy into electrical power [28-31].

The electric power output of a hydro generating unit i can be described by means of Eq. (1), which is known as the hydropower function:

$$Pp_i = 10^{-3} \times Nh_i \times Fr_i \times \rho \times g \times \eta_i \tag{1}$$

where 10^{-3} is a constant used to convert W into KW. According to Ref. [32-34], g, depends on the plant location, i.e., its latitude and elevation relative to the sea level:

$$g = 9.7803 \times \left[1 + 0.0053 \times \sin^2(\phi)\right] - 3 \times 10^{-6} \times lcr_i \tag{2}$$

The water density, ρ, is a function of the water temperature, Te, and the elevation relative to the sea level. This parameter is calculated, according to Ref. [32-34], as follows:

$$\rho = \frac{100}{\sum_{z=0}^{3} \sum_{w=0}^{3} R_{zw} \times (Te - \theta)^{w} \times \left[10^{-5}\left[\rho_0\left(1 - msm_i \times lcr_i\right) + 2 \times 10^7\right]\right]^{z-1}} \tag{3}$$

$$Nh_i = Rfl - Rtl - \left[K_0\left(\frac{q_i}{Q}\right) \times Q^2\right] - \left[K_i^{ag} \times q_i^2\right] - hll^{atm} \tag{4}$$

$$hll^{atm} = \frac{\rho_0}{\rho \times g}\left[\left(1 - msm_i \times Rfl\right)^{5.225} - \left(1 - msm_i \times Rtl\right)^{5.225}\right] \tag{5}$$

For real-time operation, the turbine hydraulic efficiency, η_i, may be determined by means of two methods, which are also detailed later. Finally, related to the hydropower function (1),

$$\eta_i = \frac{output}{input} \tag{6}$$

$accoding$ to Eq.(1),(10); thus

$$\eta_i^{min} = \frac{Pp_i^{min}}{Nh_i^{min} \times Fr_i^{min} \times g} \tag{7}$$

$$\eta_i^{max} = \frac{Pp_i^{max}}{Nh_i^{max} \times Fr_i^{max} \times g} \tag{8}$$

The turbine losses, tl_i, and the generator losses, gl_i, must be defined. The, tl_i, are obtained by field tests and may be divided into three parts: losses due to mechanical friction in the guide bearings, losses due to shaft seals, and losses due to the thrust bearing. The first one is modeled as a function of gop_i. The portion due to shaft seals is assumed constant. The losses due to the thrust bearing, bl_i, are obtained in field tests, in which a curve relating the losses with, gop_i, is obtained. The, tl_i, are divided into two parts, related to the turbine and the generator of unit i [2, 29, 35], according to equations below:

$$Dg_i = \frac{Wg_i}{Wg_i + Wt_i + Bt_i} \tag{9}$$

$$Dt_i = \frac{Wt_i + Bt_i}{Wg_i + Wt_i + Bt_i} \tag{10}$$

Considering Eqs. (9) and (10), the thrust bearing losses related to the generator, bl_i^g, and related to the turbine, bl_i^m, are defined as:

$$bl_i^g = Dg_i \times bl_i \tag{11}$$

$$bl_i^m = Dt_i \times bl_i \tag{12}$$

Considering Eq. (1), the turbine input power, tip_i, turbine output power, top_i, generator input power, gip_i, and generator output power, gop_i, are defined as:

$$tip_i = 10^{-3} \times Nh_i \times Fr_i \times \rho \times g \tag{13}$$

$$top_i = tip_i - tl_i \tag{14}$$

$$top_i = gip_i + tl_i \tag{15}$$

$$gop_i = gip_i - gl_i \tag{16}$$

Himreen lake dam (HLD) hydropower plant

Dataset Collection

Himreen lake dam small hydropower plant is located in Diyala/Iraq that serves to produce electrical power for feeding power to the people beside it. Measurements of the parameters that include upstream, downstream, net head, flow rate, and power production have been collected over a 12-year period, and the obtained data were from 1st January of 2005 to 31th December of 2016. This duration was properly acceptable, and it includes all seasons, which cover all the different possibilities in the work variables because all over the historical data are taken out on a daily reading basis. These historical data have brought and been checked from two ministries (The two ministries of water resources and electricity in Iraq) since the dams and hydropower plants are a related field between these ministries. Thus, the data used are reliable due to checked from two specific destinations. Production data of small hydropower plant (SHP) actually have a complicated and nonlinear relation and may be contained irregular and loud data. And the measurement of the variable data is commonly changed that creates values of unrelated variables [35, 36]. Main design parameters of the hydropower plant are included in Table 1.

Actual observed system operator (AOSO)

The AOSO has variable parameters of himreen lake dam (HLD) hydropower plant. Where there are some relations between them. In a direct relationship, as one variable increases, the other increases, or as one decreases the other decreases. On the other hand, the type of relationship whereby if there is a change in one variable, then there will likely be a corresponding change in the other. This is a special form of linear relationship that gives us a changing our equation of a line.

All variable parameters of hydropower plant can also be referred to as a positive relationship because this corresponding change in the other variable is typically in the same direction. Often, a special form of direct relationship called a directly proportional relationship where the variables are increasing or decreasing at the same

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rate. Figs.1 (a), and (b) shows the coordinates point on the curve of net head and flow rate vs. power production. The range of net head and flow rate vs. power production do indeed a linear relationship.

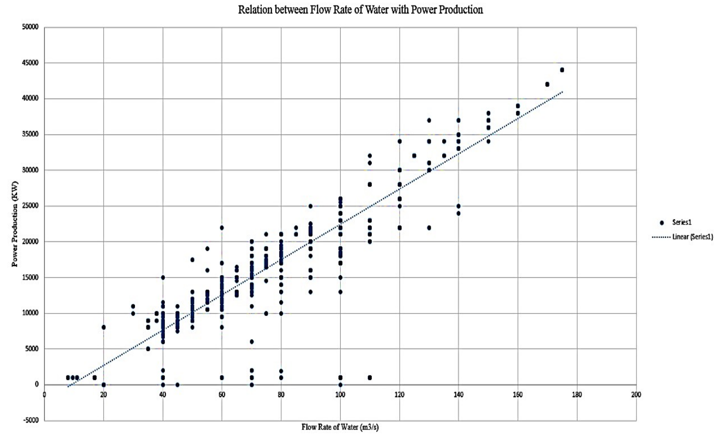

Figure 1. (a) The relationship between flow rate of water and power production

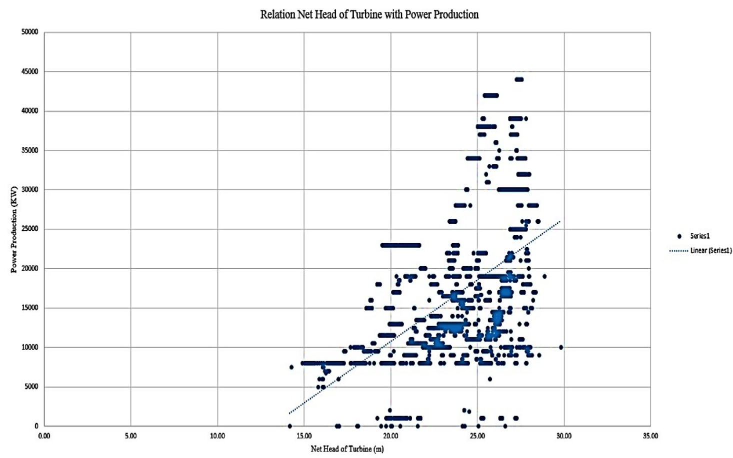

Figure 1. (b) The relationship between net head of turbine and power production

Therefore, the increase of flow rate, Fr_i^h, and net head of turbine , Nh_i^h, directly effects on power production, it can prove that by taking any different two points and compare with them. Moreover, there is an obvious relationship and direct linear proportionality with a high slope which leads to a strong increase in power production in any small change in the flow rate of water and net head of turbine when other variables are fixed as illustrated in Eq. (17) and Eq. (18).

$$Pp_i^h \propto slop\ Fr_i^h \quad (17)$$

$$Pp_i^h \propto slop\ Nh_i^h \quad (18)$$

Standard system operator (SSO) of HLD hydropower plant

The SSO built in the initial created values randomly which is corresponding to limitations of input variable parameters of hydropower system production. It's controlled by limitations which are according to standard system information. Whereas, Rand function is used for this purpose which generates a controlled random number in specific ranges. It's depending on the limitation of minimum and maximum allowed of the net head of turbine and minimum and maximum allowed of water flow rate as illustrated in Eq. (19) and Eq. (20) respectively.

$$Nh_i^s = Rand\ [Nh_i^{s,min}, Nh_i^{s,max}] \quad (19)$$

$$Fr_i^s = Rand\ [Fr_i^{s,min}, Fr_i^{s,max}] \quad (20)$$

Implementation the SSO by Matlab

The flow rate of water, Fr_i^s, Includes 4015 rows and 1 is a column. 170 is a maximum range (stop point) and 8 is a shift range or it's a (start point). Rand function generates numbers between 0 and 1. So, the 178 is the maximum range and 8 is the minimum range. Total range period is 170 from 8 to 178 as illustrated in Eq. (21). Moreover, net head of water, Nh_i^s, is also executed by rand function with a total range period is 30 from 14 to 16 as illustrated in Eq. (22). The SSO is more valuable due to it is created controlled random values with four decimal randomly depending on system standard information data [37].

$$Fr_i^s = Rand\ (4015,\ 1) * 170 + 8; \tag{21}$$

$$Nh_i^s = Rand\ (4015,\ 1) * 16 + 14; \tag{22}$$

Himreen lake dam (HLD) Application

The gravity acceleration, g, depends on the plant location, ϕ, and the runner diameter of Kaplan turbine, lcr_i, HLD hydropower plant latitude runner and its turbine diameter will be 34.187999° and 9 m respectively. Thus, the gravity acceleration, g, = 9.7966 (m^2/s) as illustrated in Eq. (2). Standard air pressure or International standard atmosphere, ρ_0, for HLD is 101,325 Pa is between 0 °C to 100 °C as well as the Constant of Materials science and manufacture, msm_i, is 2.2558×10^{-5}. There is no shutdown of the Himreen Hydropower plant and it can work continuously for all year times due to water temperature range, Te_i^h, is from 0 °C to 55 °. Moreover, the maximum water density (ρ) is 999.97 which corresponds to water temperature, Te_i^h, that equal to 4 °C.

Table 1. Main design parameters of the hydropower plant [36, 38]

Hydropower plant parameter	**AOSO / SSO**
Maximum net head of turbine (m)	29.84 / 30.8
Minimum net head of turbine (m)	14.7/14
Maximum upstream (m)	101.8
Minimum upstream (m)	92
Maximum downstream (m)	75
Minimum downstream (m)	70
Number of turbine-generating units	2
Type of turbine-generating units	Kaplan-synchronous
Number of penstocks	2
Maximum Flow (m3/s)	174 / 178
Minimum Flow (m3/s)	8/8
Power (MW)	36.4
Maximum power(MW)	44 (2×25) / 50(2×25)
Minimum power(MW)	8/8
Maximum Reservoir volume (m^3)	3.95×10^9
Minimum Reservoir volume (m^3)	1.5×10^9
Maximum hydropower efficiency	94.1
Minimum hydropower efficiency	98.9

AOSO model simulation test

Neural network performance is dependent on the model building parameters such as training. In this particular application, the trained neural network demonstrated a generalized pattern learning capability by showing high correlations and low prediction errors between pairs of actual power production efficiencies and predicted neural outputs for both training and test data sets. The next stage of the experiment is aimed at exploring the nonlinear mapping capabilities of ANNs. For the implementation of neural network models, Matlab software was used by

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exploiting its built-in design capabilities. The backpropagation neural network (BPNN) model formed 5-30-1 network structures for structures model by generating the hidden neurons necessary for nonlinear pattern mapping.

To build the artificial neural network model, first, begin to build the matrix variables that were more correlated with the variable to predict and less with each other were selected and tested for the input layer. It was decided to include the input variables to have a significant correlation with the output variable and is highly correlated between them. At this stage of the work, the variables that will form the basis for construction of the models and will study the behavior for the reporting period. This article aims to model and predict the power production.

MATLAB R2015a software is used for modeling in this research and the process of preparation of information and their use in modeling. After, defining functions for ANN modeled used, like the number of layers and neurons in different layers and creating neural networks and training networks according to defined functions. At data manager window after finishing the creation of ANN, the export and save the network model is within reach. Then, call the save network model by Matlab instruction to display the created model and testing networks according to the defined data.

Once the converged solution of the first ANN has been obtained, defining the matrix data set to let them make a creation in workspace window. The input variables have been brought to the model window to use it for test and make it as inputs which are according to a variable of Eq. (1). On other hands, The ANN modeling for predicting the power production using the net head of turbine, the flow rate of water, efficiency, and ground acceleration as first, second, third and fourth inputs to model respectively. It is sequenced correspondingly to the input variables of ANN model created form first to fourth inputs to let every input enter to same its position in ANN model created according to network inputs sequenced as mentioned before.

Afterwards, Normalized for the average density of the experimental data. The activation function here to normalize the input data to modeling for test and was deployed the logistic function (sigmoid function) with a minimum and maximum value of 0 and 1, respectively. On other hands, it is used to convert ever values of every input between 0 and 1 as illustrated in Eq. (29). Since the predictor variables have different ranges, the data were normalized and scaled down for development and testing. The normalized values were then scaled back to actual values to be displayed as output. Then, mixed these four normalized inputs to one ANN model input.

Subsequently, the power production regards as the output data of ANN model created. It is getting and stored on workspace window after applying the de-normalized mode function on its values to let them get back to its real values as illustrated in Eq. (30). This is continued for all variables deemed to have a significant impact on the SHP modeling. These steps can be repeated as long as relevant variables are available. For example, if in the future the SHP-is characterized, this parameter could be modeled without having to repeat the entire process.

In general, the creation of ANN model should correspond exactly the actual model virtually in principles of its affections', parameters' and times' so as to get the typical model. Firstly, Entire time is regarding as the modeling time totally in simulation, which indicates to the extent of the total time for twelve years. Since there are input-output variables data has been observed daily and every day is equal to 1440 minutes. Thus, the entire time is started from 1440 minutes for the first day. It continues increasingly until it arrives at (4.5×10^6) minutes, which is equivalent to the total time in minutes. Secondly, the main reason for using the transport delay is making the ANN model to account the entire model time by increasing daily time in minutes which equals to every 1440 minutes.

Fuzzy logic controller (FLC)

Fuzzy set theory and fuzzy logic establish the rules of a nonlinear mapping. The use of fuzzy sets provides a basis for a systematic way for the application of uncertain and indefinite models. Fuzzy control is based on a logical system called fuzzy logic. It is much closer in spirit to human thinking and natural language than classical logical systems [31, 39]. An FL system mainly consists of three steps: fuzzification, fuzzy inference, and defuzzification. In the fuzzification step, the real variables are translated into linguistic variables by using fuzzy set theory. In the fuzzy inference step, ‘If–Then’ rules that define the system behavior are evaluated. The defuzzification step translates the linguistic result obtained from the fuzzy inference into a real value by using the rule base provided [40, 41].

This strategy simply intends to manipulate, at low cost and in normal condition. No predictive control is involved, and it works just with a direct relation between the net head of turbine and the flow rate of water. It provides a constant output flow for a long time. When the net head is high, the flow rate still provides a constant value. However, after a while, the normal conditions cannot be respected. When the net head reaches a too high level, the constant output value suffers. Therefore, it takes a long period of time to cope with big change in flow rate. Another problem appears when the turbine has a low net head. Then, the constant flow rate consumes the water, so the net head in the equalization reaches a very low level. In this case, the strategy used in solve this problem by making the flow rate equal to the constant net head.

The strategy proposed in this article uses an FLC solves all previous problems. It provides a constant output value of power generation with in all normal conditions of the net head and flow rate. In this way, the FLC within this strategy takes into consideration the net head in addition to providing flow rate value as possible as when conditions allow that. Moreover, the proposed system has a fuzzy rule-based operation model for a dual hydropower reservoir which is robust and easy to use by the operators. Generally, the fuzzy rules are formed based on the actual historical operation of the reservoir and expert knowledge. The model provides a reliable knowledge base for optimum operation of the nominated hydropower reservoir. The methodology for building the fuzzy rule-based model is independent of the method employed for expert knowledge base generation.

Proposed fuzzy artificial neural network (FANN)

The main objective of the control system is to determine the effectiveness of the proposed FLC by reducing the complexity of tuning membership function (MF) for high-performance power generation by providing that the suitable the main two inputs parameters; net head of turbine and flow rate of water depending on the operating conditions. Researchers studied that triangular type of MF is the best for FLC drive system. Therefore, in this study, FANN is considered using triangular MF type for single input and dual outputs as shown in Fig. 2.

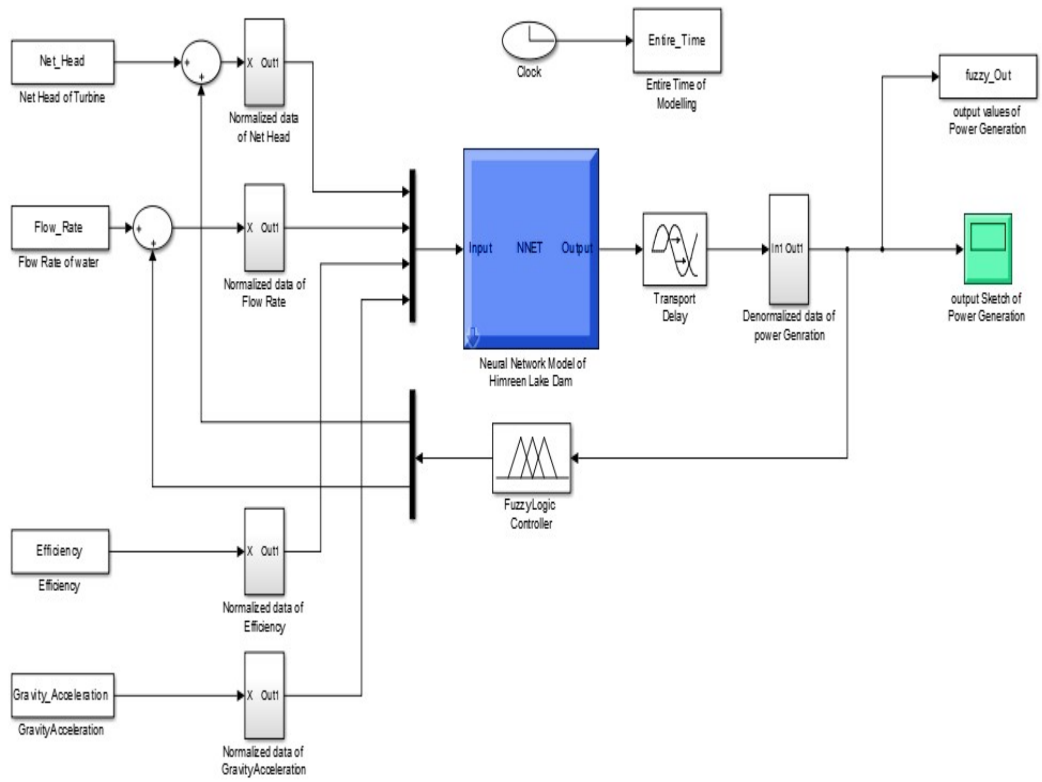

Figure 2. Architecture of the fuzzy artificial neural network (FANN) modeling in testing process

Scenario; right-angle fuzzy artificial neural network (RFANN)

The changing in input/output parameters according to fuzzy membership makes the minimized FLC suitable for a high range of disturbances, but this method it not suitable for highly complex systems, which need different triangular shapes. Therefore, a method to change the fuzzy input/output parameters according to the optimal shape and boundaries of the membership is required to control high nonlinear systems such hydropower generation control. Right angle triangle membership function may be used to overcome the above-stated problem. The parameters right angle triangle membership functions are modified to improve the power generation behavior especially in the vicinity of the set point. The concept of RFANN controller is to get optimum tuning of membership function by assuming the symmetrical triangular fuzzy-number distribution of the parameters and variables. The membership function for the maximum hydropower operation decided based on the historical data for the maximum net head, flow rate, and power generation. Tuning the width and moving the peak value positions of these right-angle triangle membership functions towards the positive big (PB) value will cause the stability control to be more sensitive to a small change in power generation error and produce a large control. On the other hand, its head always towards to maximum and final position for the input/output parameters which is leading to get an optimum outcome.

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The membership in Fig.3 is the real membership after conversion. Its shape developed using right-angle which is create a change on the top of the triangle membership function. Fig.3 represents the membership function of flow rate variable and the machinery of crushing and shrinking its values to be bounded between -1 and 1. Repeatedly there is an ability to reapply again same rules on the other variables like net head and power generation.

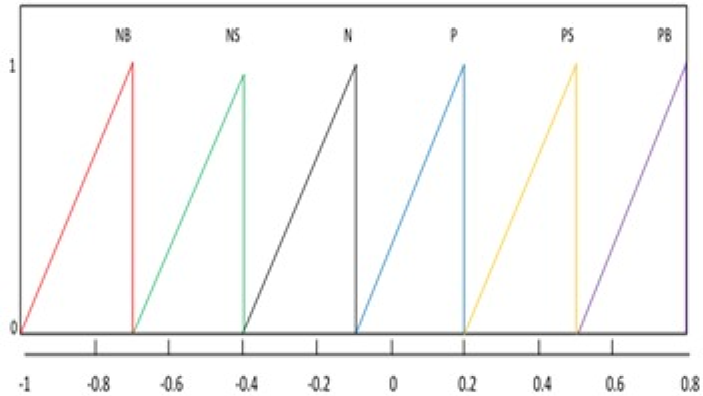

Figure 3. Right-Angle Triangle Membership functions for Flow Rate

The RFANN method can be applied for a high level of complexity because it gives suitable shape and boundaries for the fuzzy system without needing to change in fuzzy memberships. Moreover, it can be applied for any other membership. It obviously takes less calculation time for the input-output parameters with respect to minimizing fuzzy as well as it doesn't cause increasing the NFA matrix. RFANN controller is less complexity comparing with conventional- FLC, which gives best results.

III. Results and Discussion

In the third part of the study, in order to assess the ability of fuzzy artificial neural network (FANN) model using the best inputs combination selected in the first application. With a brief theory on the FANN modeling concept given in above section, the objective of this work is to obtain hydropower operation with optimal value and zero fluctuation from employ three contributions on the FANN model. The network used in the fuzzy inference system was a Mamdani type model, which creates fuzzy rules systematically depending on tuning input–output parameters, then, developed by NFA and right-angle triangle membership function. The three control methods mentioned earlier are simulated by MATLAB software. The preceding testes derived from on the FANN models using the AOSO firstly and then the SSO also as input signals, the expected output of the system should also get the optima control and operation point in a stable manner.

Some additional tests were performed around several operating points. They prove the precision degree for each proposed FANN model. It shows the validation of the developed approaches for large operating points. Response curves of three control methods are indicated in Fig.4, in which curve 3 represents the right-angle triangle membership functions fuzzy artificial neural network (RFANN).

Simulation results of the RFANN controller which was come from combining right-angle triangle membership function fuzzy neural network with the NFA are characterized by reliability, it is robust and requires nothing for adjusting the parameter of RFANN control. The capacity of global optimization of its own firefly algorithm and the new shape of the membership function, allows the system to track the maximum expected output generation properly as shown in Fig.4.

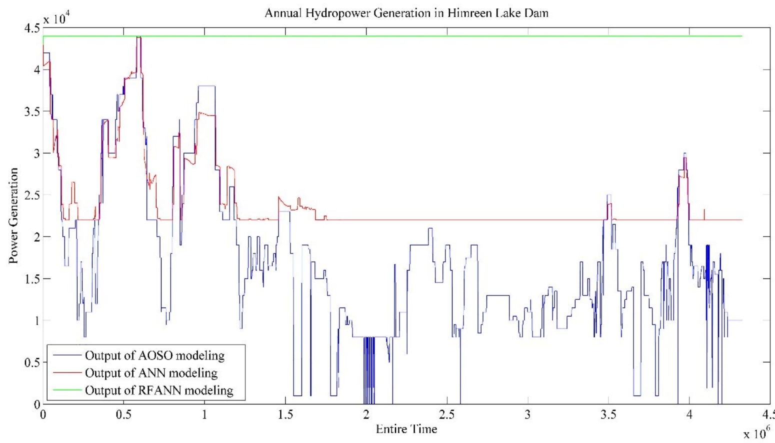

Figure 4. Hydropower generation of RFANN against AOSO and ANN model

However, as explained in methodology all case values of hydropower generation get to the optimal point which is 44 MW achieves the goal of proposed control. The range of hydropower generation variation for AOSO, ANN model, and RFANN model are (0 to 44), (22 to 44), (44 to 44) MW respectively. Since total count observed values used for testing is 4015. True positive is a count of all the correctly classified normal values which regard as a number of hydropower generation cases which get to the optimal point. The true negative is a count of all the correctly classified abnormal values which regard as a number of hydropower generation cases which don't get to the optimal point. The true positive values of AOSO, ANN model, and RFANN model are 401, 401, 4015 respectively. Therefore, the accuracy ratio which achieves the goal of hydropower generation is 10%, 10%, 100% respectively as shown in Eq. (40).

$$\text{Accuracy (\%)} = \frac{True\ \ Positive}{True\ \ Positive + True\ \ Negative} \times 100 \quad (40)$$

IV. Conclusion

In this study, two new fuzzy artificial neural network (FANN) models to stabilize annual hydropower operation have been proposed. The generalized FANN model was applied to describe the hydro generation in the presence of input random variables. The experimental and simulation results of the proposed FANN models show the performances and flexibilities for the modeling based on this approach. According to the hydro generation stability theory, there are some scenario tests, which illustrated in the results section. It has presented to show the exactness of the proposed fuzzy models compared with the output result of the AOSO and ANN model. Besides, the proposed approach can also be adapted to different hydroelectric power plant systems by applying simple test methods. Those models can be very useful for synthesizing suitable robust controllers for hydro generation. The robust controllers ensure a good power quality of the system. Especially, when the proposed annual hydropower operation model is used in the closed loop. In addition, the proposed approximations permit the researchers interested in the SHP control to benefit from growth technologies in digital calculators which make synthesis robust controllers easier.

V. Nomenclature

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h Actual Observed System Operator

s Standard System Operator

parameters

Pp_i electrical power production (KW)

g gravity acceleration (m/s^2)

η_i turbine effeciency

ϕ latitude of hydropower plant (°)

lcr_i elevation of the turbine rotor (m)

ρ water density ($\mathrm{kg/m^3}$)

R_{zw} element (z, w) of the matrix of coefficients that relates with T($\mathrm{kg/m^3}$)

θ constant with value 0 if 0 <Te <20 or 20 if 20 < Te < 50 (.C)

T water temperature in the reservoir (.C)

Rfl reservoir forebay level (m)

Rtl reservoir tailrace level (m)

K_0 theoretical coefficient associated with the load losses in the canalintake ($\mathrm{s^2/m^5}$)

Q plant turbined outflow ($\mathrm{m^3/s}$)

K_i^{ag} aggregated coefficient of hydraulic load losses ($\mathrm{s^2/m^5}$)

hll^{atm} atmhydraulic losses due to the difference of atmospheric pressure between Rfl and Rtl (m)

bl_i thrust bearing losses (MW)

Bt_i turbine hydraulic thrust (N)

Dg_i portion of thrust bearing losses referent to the generator

Dt_i portion of thrust bearing losses referent to the turbine

Wg_i generator weight (N)

Wt_i turbine weight (N)

tip_i turbine input power

top_i turbine output power

gip_i generator input power

gop_i generator output power

tl_i turbine loss

gl_i generator loss

Nh_i^{min}, Nh_i^{max} minmaum and maximum net head

Fr_i^{min}, Fr_i^{max} minimum and maximum flow rate of water

References

[1] A. S. M. Priyadharson, R. Ganesan, and P. K. Surarapu, "PLC – HMI Automation Based Cascaded Fuzzy PID for Efficient Energy Management and Storage in Real Time Performance of a Hydro Electric Pumped Storage Power Plant," Procedia Technology, vol. 21, pp. 248-255, 2015/01/01/ 2015.

[2] B.Bazartseren, G. Hildebrandt, and K. P. Holz, "Short-term water level prediction using neural networks and neuro-fuzzy approach," Neurocomputing, vol. 55, pp. 439-450, 2003/10/01/ 2003.

[3] B. Kurtulus and M. Razack, "Modeling daily discharge responses of a large karstic aquifer using soft computing methods: Artificial neural network and neuro-fuzzy," Journal of Hydrology, vol. 381, pp. 101-111, 2010/02/05/ 2010.

[4] M. Cobaner, B. Unal, and O. Kisi, "Suspended sediment concentration estimation by an adaptive neuro-fuzzy and neural network approaches using hydro-meteorological data," Journal of Hydrology, vol. 367, pp. 52-61, 2009/03/30/ 2009.

[5] J. Shiri and O. Kisi, "Short-term and long-term streamflow forecasting using a wavelet and neuro-fuzzy conjunction model," Journal of Hydrology, vol. 394, pp. 486-493, 2010/11/26/ 2010.

[6] R. Tanha Aminloei and S. F. Ghaderi, "Generation planning in Iranian power plants with fuzzy hierarchical production planning," Energy Conversion and Management, vol. 51, pp. 1230-1241, 2010/06/01/ 2010.

[7] Y. Xu, J. Zhou, X. Xue, W. Fu, W. Zhu, and C. Li, "An adaptively fast fuzzy fractional order PID control for pumped storage hydro unit using improved gravitational search algorithm," Energy Conversion and Management, vol. 111, pp. 67-78, 2016/03/01/ 2016.

[8] F.-w. Xie, Y.-f. Hou, Z.-p. Xu, and R. Zhao, "Fuzzy-immune control strategy of a hydro-viscous soft start device of a belt conveyor," Mining Science and Technology (China), vol. 19, pp. 544-548, 2009/07/01/ 2009.

[9] K. Lal, A. K. Barisal, and M. Tripathy, "Grey Wolf Optimizer Algorithm Based Fuzzy PID Controller for AGC of Multi-area Power System with TCPS," Procedia Computer Science, vol. 92, pp. 99-105, 2016/01/01/ 2016.

[10] S. Baghya Shree and N. Kamaraj, "Hybrid Neuro Fuzzy approach for automatic generation control in restructured power system," International Journal of Electrical Power & Energy Systems, vol. 74, pp. 274-285, 2016/01/01/ 2016.

[11] S. Prakash and S. K. Sinha, "Simulation based neuro-fuzzy hybrid intelligent PI control approach in four-area load frequency control of interconnected power system," Applied Soft Computing, vol. 23, pp. 152-164, 2014/10/01/ 2014.

[12] R. Moeini, A. Afshar, and M. H. Afshar, "Fuzzy rule-based model for hydropower reservoirs operation," International Journal of Electrical Power & Energy Systems, vol. 33, pp. 171-178, 2011/02/01/ 2011.

[13] R. U. Kamodkar and D. G. Regulwar, "Optimal multiobjective reservoir operation with fuzzy decision variables and resources: A compromise approach," Journal of Hydro-environment Research, vol. 8, pp. 428-440, 2014/12/01/ 2014.

[14] B. Wang, J. Xue, F. Wu, and D. Zhu, "Robust Takagi-Sugeno fuzzy control for fractional order hydro-turbine governing system," ISA Transactions, vol. 65, pp. 72-80, 2016/11/01/ 2016.

[15] A. El hamdaouy, I. Salhi, A. Belattar, and S. Doubabi, "Takagi–Sugeno fuzzy modeling for three-phase micro hydropower plant prototype," International Journal of Hydrogen Energy, vol. 42, pp. 17782-17792, 2017/07/13/ 2017.

[16] N. Kishor, "Zero-order TS fuzzy model to predict hydro turbine speed in closed loop operation," Applied Soft Computing, vol. 8, pp. 1074-1084, 2008/03/01/ 2008.

[17] J. Liu, F.-l. Chung, and S. Wang, "Bayesian zero-order TSK fuzzy system modeling," Applied Soft Computing, vol. 55, pp. 253-264, 2017/06/01/ 2017.

[18] C. Affonso, R. J. Sassi, and R. M. Barreiros, "Biological image classification using rough-fuzzy artificial neural network," Expert Systems with Applications, vol. 42, pp. 9482-9488, 2015/12/30/ 2015.

[19] S. Shinde and U. Kulkarni, "Extended fuzzy hyperline-segment neural network with classification rule extraction," Neurocomputing, vol. 260, pp. 79-91, 2017/10/18/ 2017.

[20] C. M. Yeşilkanat, Y. Kobya, H. Taşkın, and U. Çevik, "Spatial interpolation and radiological mapping of ambient gamma dose rate by using artificial neural networks and fuzzy logic methods," Journal of Environmental Radioactivity, vol. 175, pp. 78-93, 2017/09/01/ 2017.

[21] B. D. Barkana, I. Saricicek, and B. Yildirim, "Performance analysis of descriptive statistical features in retinal vessel segmentation via fuzzy logic, ANN, SVM, and classifier fusion," Knowledge-Based Systems, vol. 118, pp. 165-176, 2017/02/15/ 2017.

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[22] M. K. Goyal, B. Bharti, J. Quilty, J. Adamowski, and A. Pandey, "Modeling of daily pan evaporation in sub tropical climates using ANN, LS-SVR, Fuzzy Logic, and ANFIS," Expert Systems with Applications, vol. 41, pp. 5267-5276, 2014/09/01/ 2014.

[23] B. Wang, T. Man, and H. Jin, "Prediction of expansion behavior of self-stressing concrete by artificial neural networks and fuzzy inference systems," Construction and Building Materials, vol. 84, pp. 184-191, 2015/06/01/ 2015.

[24] M. Rafie and F. Samimi Namin, "Prediction of subsidence risk by FMEA using artificial neural network and fuzzy inference system," International Journal of Mining Science and Technology, vol. 25, pp. 655-663, 2015/07/01/ 2015.

[25] A. T. Hammid, A. Bhardwaj, and S. Prakash, "Design Remote Power Control I/O Data Acquisition System and Control on Home Automation," IJECCE, vol. 4, pp. 528-535, 2013.

[26] S. Roy, A. K. Das, V. S. Bhadouria, S. R. Mallik, R. Banerjee, and P. K. Bose, "Adaptive-neuro fuzzy inference system (ANFIS) based prediction of performance and emission parameters of a CRDI assisted diesel engine under CNG dual-fuel operation," Journal of Natural Gas Science and Engineering, vol. 27, pp. 274-283, 2015/11/01/ 2015.

[27] K. Bouhoune, K. Yazid, M. S. Boucherit, and A. Chériti, "Hybrid control of the three phase induction machine using artificial neural networks and fuzzy logic," Applied Soft Computing, vol. 55, pp. 289-301, 2017/06/01/ 2017.

[28] A. T. Hammid, M. Hojabri, M. H. Sulaiman, A. N. Abdalla, and A. A. Kadhim, "Load Frequency Control for Hydropower Plants using PID Controller," Journal of Telecommunication, Electronic and Computer Engineering (JTEC), vol. 8, pp. 47-51, 2016.

[29] R. Hemmati and H. Saboori, "Short-term bulk energy storage system scheduling for load leveling in unit commitment: modeling, optimization, and sensitivity analysis," Journal of Advanced Research, vol. 7, pp. 360-372, 2016/05/01/ 2016.

[30] G. A. Kovalenko, L. V. Perminova, N. A. Rudina, Y. G. Maksimova, and A. Y. Maksimov, "Sapropel-based supports as novel macroporous carbon-mineral adsorbents for enzymatic active substances," Resource-Efficient Technologies, vol. 2, pp. 159-167, 2016/12/01/ 2016.

[31] A. T. Hammid, "Applications of Tuning Control Actions for the Efficient Load/frequency Control in Steam Turbine," International Journal of Current Engineering and Technology, vol. 3, pp. 1895-1898, 2013.

[32] I. E. Commission, "Storage Pumps and Pump-turbines – Model Acceptance tests," IEC 60193, 1999.

[33] A.T. Hammid and M. H. Sulaiman, "Optimal Long-Term Hydro Generation Scheduling of Small Hydropower Plant (SHP) using Metaheuristic Algorithm in Himreen Lake Dam," in MATEC Web of Conferences, 2017, p. 04017.

[34] A.T. Hammid, M. H. B. Sulaiman, and A. A. Kadhim, "Optimum Power Production of Small Hydropower Plant (SHP) using Firefly Algorithm (FA) in Himreen Lake Dam (HLD), Eastern Iraq," Research Journal of Applied Sciences, vol. 12, pp. 455-466, 2017.

[35] A.T. Hammid, "Direct on Line Starter Motor and Reverse System in Allen-Bradley PLC," Diyala Journal for Pure Sciences (DJPS), vol. 12, pp. 132-148, 2016.

[36] A.T. Hammid, M. H. B. Sulaiman, and A. N. Abdalla, "Prediction of small hydropower plant power production in Himreen Lake dam (HLD) using artificial neural network," Alexandria Engineering Journal, 2017/01/07/ 2017.

[37] G. Sethi, B. S. Saini, and D. Singh, "Segmentation of cancerous regions in liver using an edge-based and phase congruent region enhancement method," Computers & Electrical Engineering, vol. 53, pp. 244-262, 2016/07/01/ 2016.

[38] K.Ahmad-Rashid, "Present and Future for Hydropower Developments in Kurdistan," Energy Procedia, vol. 112, pp. 632-639, 2017/03/01/ 2017.

[39] J.Mohanalin, P. K. Kalra, and N. Kumar, "Microcalcification segmentation using normalized tsallis entropy: an automatic “q” calculation by exploiting type II fuzzy sets," IETE Journal of Research, vol. 55, pp. 90-96, 2009.

[40] B. Ponnapalli and P. Natarajan, "Harmonic Level Minimization Using Neuro–Fuzzy-Based SVPWM," IETE Journal of Research, pp. 1-16, 2017.

[41] G. Prabhakar, S. Selvaperumal, and P. Nedumal Pugazhenthi, "Fuzzy PD Plus I Control-based Adaptive Cruise Control System in Simulation and Real-time Environment," IETE Journal of Research, pp. 1-11, 2017.