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Research paper

Modeling and design of an automatic generation control for hydropower plants using Neuro-Fuzzy controller

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ABSTRACT

This paper presents the modeling, design, and experimental analysis of an Automatic Generation Control (AGC) for a hydropower plant using Adaptive-Neuro-Fuzzy Inference system (ANFIS). This was aimed at reducing the frequency deviations which occur during power generation. The Adaptive-Neuro-Fuzzy Inference system (ANFIS) was used to intelligently control the selection of parameters for the effective control of power in the hydropower plant. The proposed ANFIS was trained with input–output data of the fuzzy logic controller (FLC). The ANFIS model is used as a hybrid learning model which includes the Least Square Estimate (LSE) and back propagation algorithm (BPA). The conventional PID, FLC, and ANFIS controllers were investigated using MATLAB. In order to determine the best controller, the controllers were experimented and compared to determine the controller with the best performance. The results show that frequency deviations occur as a result of a continuous variation of loads, which make the deviations difficult to control when a governor is not applied. Furthermore, the response of the AGC of the hydropower plant (in the single and double area) with step load changes was studied. The simulation results show that the ANFIS controller performs better compared to the PID as well as the FLC. Further results indicate that the proposed ANFIS controller helps to speed up the performance of the AGC of the hydropower plant. The ANFIS controller not only improved the performance but also made the fuzzy inference system (FIS) less dependent on the expert system.

1. Introduction

Hydropower is one of the main sources of power generation. It is generated, transmitted, and distributed in the form of electricity to satisfy all kinds of power demands. The importance of a steady supply of power in all the sectors of a country's economy cannot be overemphasized (Duquea et al., 2016; Kichonge, 2018). Generally, electrical power plants are inter-linked to supply sustainable, quality as well as an economical operation of each generation unit.

The main responsibility of each unit is to supply the necessary power to meet the users power demand (Mishra et al., 2011; Ramos et al., 2000; Yildiz and Vrugt, 2015). In a power system, a single generator can feed large and complex areas with the aid of inter-linked plants. The supply of power to neighboring companies is achieved through a Tie line power transfer mechanism.

Now days, the generation of electrical power is not sufficient to cater for the increasing load demand due to the mismatch between load and generation. Frequency and voltage are the key parameters in a hydropower plant, and controlling them is a major concern. The frequency depends on the real power generation, and it should be balanced and remain constant in different operating conditions (Ang, 2005; Akuma, 2018). In grid hydropower plants, a change in active power generation at one power line affects the whole system's frequency. In general, the quality of a hydropower plant depends on its frequency which needs to be regulated properly for quality power supply. Usually, excitation voltage control and load frequency control (LFC) are non-interactive and can be modeled and analyzed independently (Working Group Prime Mover and Energy Supply, 1992). Most of the LFC research problems are mainly on thermal–thermal, with a few papers on Hydro-thermal power plants. Hydro-hydropower (two area hydropower) systems have not been given much attention in previous works (Ding and Sinha, 2011). The use of fuzzy systems have been used in some studies (Shah et al., 2012; Gheisarnejad and Khooban, 2019). These systems cannot make predictions like neural networks. Based on the literatures reviewed, the main

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difficulty discovered is with the conventional-based speed rotation regulation. Some of the challenges include slow response of the governor system to return back to the nominal value after frequency disturbance has occurred in the plant. The purpose of using an ANFIS is to combine the parallel computations of the learning capacities of artificial neural networks (ANN) and fuzzy expert systems (Shah et al., 2012). The neural capabilities of the hybrid technique (ANFIS) make it able to give accurate predictions based on the input–output data which was collected from the plant. The ANFIS control can be used to control the response of the two area as well as that of the single area hydropower plant by combining ANFIS based governor controlling techniques (Ismail and Hassan, 2012).

This work presents the modeling of an AGC of a hydropower plant and also evaluates the performance of the conventional (PID) controller, fuzzy logic controller (FLC), as well as the proposed ANFIS controller. The main objectives of the proposed automatic generation control (AGC) are: regulate the system frequency to a specified nominal value, maintain power interchange, as well as maintain a stable change in generation among units. Different frequency control strategies are used in a load dispatch center (LDC), and the frequency control mode of the control area is mainly classified as: Tie line bias control (TLBC), Flat tie-line control (FTLC), or Flat frequency control (FFC) (Rajeswari et al., 2012; Gheisarnejad and Khooban, 2019). A control system in a hydropower plant is essential to cancel the effects of random load changes, and to keep the systems frequency within a standard range (50 Hz or 60 Hz). Too much supply increases the systems frequency and too much demand decreases the systems frequency (Chang et al., 2017; Bizon et al., 2013).

1.1. Statement of the problem

The development of a giant generator for a hydropower plant does not resolve the mismatch between load and generation of power caused as a result of increasing demand of energy. In a hydropower system, there are a lot of utilities that interconnect each other and exchange power with neighboring plants using Tie lines. One of the challenges of interconnected hydropower plants is maintaining their nominal frequency. For a huge hydropower plant, the primary concern is power generation as changes in load cause a steady-state frequency change depending upon the governor's droop characteristics as well as the sensitivity of the load frequency. Errors in frequency which occur during power generation are not avoidable, therefore, maintaining a steady generation frequency and tie-line flow at a desired range is difficult. This power imbalance leads to frequency deviation, but may also cause a blackout. Most times, a PID controller is applied to regulate the AGC of the hydropower plant. It usually takes in a slow response which makes the system unstable. Also, a number of works have suggested the use of FLC for hydropower plant power improvement. In addition, Hydro-hydropower plants have not been given much attention in recent times.

The remaining parts of this paper are structured as follows: Section 2 presents the related works, while Section 3 describes the modeling of the hydropower plant. Section 4 describes the controller design and Section 5 presents the findings obtained, and afterward the results are discussed. This is accompanied by a conclusion and suggestion for future work in Section 6.

2. Related works

This section presents the literatures related to load frequency control (LFC). In Jagatheesan and Anand (2014), a three area hydro-thermal power system with electric and mechanical governors was proposed to control load frequency. The performance of the AGC proved that an electrical governor is better compared to a mechanical governor with and without generator rate constraints. Similarly, when an integral and PI controller was applied to an AGC, the result show that the PI controller gives a minimum damping oscillation with good settling time compared to the Integraller (I) controller with and without considering non-linearity. Although, these controllers have good dynamic responses and are also easily implemented, they are not efficient in the case of an uncertain and complex system. Furthermore, electrical governors heat water and the constitutes of the water are most times lost; therefore the water cannot be used for other purposes such as irrigation and fish production.

In Chahar and Panwar (2016), a fuzzy tuned PID controller was proposed for thermal power plants. The results show that the controller achieves a better performance as compared to the conventional controllers. The authors also observed that the system was not capable of adapting to variations in system behavior.

In Chaudhary and Singh (2017), an intelligent controller was applied for an AGC of an interconnected hydropower plant. Both FLC and ANN were compared with the conventional controller. The results show better performance of ANN and FLC as compared to the PID controller. Sultan (2016) employed the use of particle swarm optimization (PSO) technique for tuning of conventional PID gain. A comparison was made with other methods and the PSO technique was found to achieve a better performance, although the PID controller was easier to design. The authors in Annam (2017) investigated AGC of interconnected power plants and showed their performance for different controllers such as PI, PID, and fuzzy PI controller. The performance of the AGC with Fuzzy PI controller showed superior performance compared to that of the PI controller.

In Leu (2018), the performance of two area hydropower plants for an AGC was investigated with different controllers such as PID, FLC, and ANN for optimal control. The performance of the AGC with FLC gave better results compared to the AGC with PID control in the case of a single area hydropower plant. In addition, an ANN was trained using data generated from optimal controller simulation results and the trained ANN model was used to track the optimal performance of the hydropower plant. The trained ANN model has large settling time and steady-state error. Besides this, the authors did not compare the fuzzy logic and ANN model as well as their combined effects.

In Xiomara and Soares (2017), an optimal controller concept was applied for large power plants with the aim of improving the performance of the plant. The authors stated that the realization of the controller was difficult, cumbersome, as well as expensive because of the feedback parts of the optimal controller are expressed completely in terms of the function of the state vector of the plant.

Different methods have been proposed in literature to improve the performance of hydropower plants operation such as Jagatheesan and Anand (2014), Chahar and Panwar (2016), Chaudhary and Singh (2017), Sultan (2016), Annam (2017), Leu (2018) and Xiomara and Soares (2017). In most of the literatures reviewed, it was observed that in some cases AGC using FLC gave better results compared to the AGC using other controllers, and in other cases, the other controllers performed better than the FLC. Therefore, this paper presents the modeling, design and experimental analysis of an AGC for a hydropower plant using Adaptive-Neuro-Fuzzy Inference system (ANFIS) with the aim of reducing the frequency deviations which occur during power generation and also to improve the controller's performance. Furthermore, unlike other papers which only carried out experiment on only a single area hydropower plant; in this paper, we performed experiments on both the single area hydropower plant and the two area hydropower plant.

3. Modeling of the hydropower plant

The variation in speed of a hydropower plant is detected by a turbine speed governor which is used to regulate the input of the valve of the turbine. Water enters into the turbine through a pipe that is particularly obstructed by the valve gate. Typically, turbine speed governing includes Fly ball governing. It is used to detect a change in speed of the generator. Hydraulic amplifiers comprise of a pilot valve and dominant piston arrangement. This is important to regulate the water valve against high-pressure water, while the linkage mechanism provides feedback from the gate valve. The speed changer is used to provide a steady output power (Pritam et al., 2017; Ullah et al., 2021; Si et al., 2018). The equation of the water gate is given as:

$$\Delta X_E(s) = \left[\Delta P_C(s) - \frac{1}{R}\Delta f(s)\right]\frac{K_H}{1+sT_H} \tag{1}$$

where $\frac{K_H}{1+sT_H}$ is the governor speed gain, $R = \frac{K_1}{K_2}$, is the speed regulation of the governor, $T_H = T_1 =$ Governor time constant, and $\Delta X_E(s) = \Delta P_{GC}(s)$ is the gate position.

Since the governor itself does not generate enough force to operate the water valve, a single hydraulic servo motor was used between the governor and the valve. The transfer function (TF) of the various building blocks for the water speed governor were put together as shown in Fig. 1. The parameters, descriptions, and values of the hydropower plant models for Area 1 and Area 2 are presented in Table 1.
where, T_P is the pilot valve and servomotor time constant,
K_S is the servo gain,
R_P is the permanent droop,
R_T is known as the tangent droop,
T_R is the Rest time, R_T is the Tangent Droop, T_G is the Main servo time constant. The value of R_P determines the slope of the governor characteristics. The generalized TF model for governing hydropower plants is given by Fig. 2.
P_O is the Reference power setting, ΔP is the change in power, K is the gain of the governor, and Δw is the speed deviation, T_2 is the Transient droop time constant, T_3 is the Main servo time constant, P_{GV} is the Gate valve, and T_1 is the speed governor rest time.

3.1. Hydro-turbine modeling

The tangent characteristic of a hydro-turbine is determined by the dynamics of water flowing through the penstock. Since the system is exposed to a small change during its normal working operation, the linear model is sufficient for the dynamic representation of the hydro-turbine as given by Eq. (2) (Saha and Saikia, 2018).

$$\frac{\Delta P_M}{\Delta G} = a_{13}\frac{1 + (\mathrm{a}_{11} - \mathrm{a}_{13}\mathrm{a}_{21}/\mathrm{a}_{23})\,\mathrm{sT}_w}{1 + \mathrm{a}_{11}\mathrm{sT}_w} \tag{2}$$

ΔP_M—Mechanical time constant, ΔG—Gate position, and T_W—water time constant. For an ideal Francis type turbine after substituting the coefficients in Eq. (2), a generalized transfer function of the hydro-turbine model is obtained. This is shown in Fig. 3.

3.2. Synchronous generator modeling

A generator in a hydropower plant is used to aid the hydraulic power unit to spin the turbine which enables energy generation. A mechanical torque is applied to increase rotations, while an electrical force is used to reduce rotation. When an electrical load rises a mechanical torque less than the electrical torque, it causes the entire rotation of the system to start to decrease. Therefore, it is necessary to restore the mechanical torque to its equilibrium point. Eq. (3) represents the dynamics of the synchronous generator which includes the total inertia of the power plant.

$$\Delta w_r = \frac{1}{Ms + D}[\Delta P_m - \Delta P_e] \tag{3}$$

where D- is the Damping constant,
M- is the Inertia constant of the generator,
Δw_r- is the per unit value of the angular velocity,
ΔP_m- is the change in mechanical power output, and
ΔP_e- is the change in electrical power output.

3.2.1. Single area hydropower plant

The main responsibility of an AGC in an isolated hydropower plant is to maintain the nominal frequency. The LFC of an isolated hydropower plant is shown in Fig. 4, while the frequency response for the single area hydropower plant is shown in Fig. 5.

3.2.2. Two area hydropower plant

Generators which are closely coupled internally, and tend to have similar response characteristic are not coherent. Therefore, it is possible to use LFC loop in all systems in the control area. An important part of Grid power plants is that generators make the plants response to vary in rotation speed via a governor control. The block diagram for the two area (hydro-hydropower) plant is shown in Fig. 6.

3.3. Modeling of tie line

The equations used to model the tie lines are given by Eqs. (4) and (5).

$$\Delta P_{12}(s) = \frac{2\pi T}{s}[\Delta f_1(s) - \Delta f_2(s)] \tag{4}$$

$$\Delta p_{tieij}(s) = \frac{1}{s} * T_{ij} * (\Delta f_i(s) - \Delta f_j(s)) \tag{5}$$

where $\Delta p_{tieij}(s)$-Tie line power between ith and jth area, and T_{ij}-Tie-line synchronizing torque coefficient of ith and jth areas. ACE1 and ACE2 are the linear combinations of frequency and Tie line power error. The area control error (ACE) of the interconnected power plants is given by Eqs. (6)–(8).

$$ACE_i = \sum_{j=\cdots .n, j\neq 1} \Delta \mathrm{P_{tieij}} + \mathrm{B_i}\Delta \mathrm{f_i} \tag{6}$$

$$\mathrm{ACE_1} = \Delta \mathrm{P_{12}} + \mathrm{B_1}\Delta \mathrm{f_1} \tag{7}$$

$$\mathrm{ACE_2} = \Delta \mathrm{P_{21}} + \mathrm{B_2}\Delta \mathrm{f_2} \tag{8}$$

$\mathrm{ACE_1}$-Area control error for area 1, $\mathrm{ACE_2}$- Area control error for area 2, and $\mathrm{B_i}$-Composite frequency gain.

4. PID controller design

Automatic Generation Control (AGC) is mostly used in conventional PID control systems (Saha and Saikia, 2018). It calculates the error value as the difference between a measured process variable (actual plant output) and the desired set point. It also attempts to reduce deviations by adjusting manipulated variables. Generally, they are mostly used in industrial processes because of their numerous advantages such as ease of operation by plant operators and has a near to the desired optimal performance, and a wide range of applicability. Mathematically, an AGC can be represented by Eq. (9).

$$u(t) = K_P e(t) + k_I \int_0^t e(t).dt + k_D \frac{de(t)}{dt} \tag{9}$$

Table 1
Parameters, descriptions, and values of the hydropower plant models.

Parameters	Description of parameters	Value	Unit
B_1 and B_2	Tie line frequency bias in Area 1 and Area 2	0.425	P.u. MW/Hz
R_1 and R_2	Governor gain regulation for Area 1 and Area 2	2.4	Hz/P.u. MW
K_{P1} and K_{P2}	Power plant gain constant in Area 1 and Area 2	120	Hz/P.u. MW
T_{P1} and T_{P2}	Power plant time constant in Area 1 and Area 2	20	s
T_{12}	Tie line synchronization coefficient for Area 1 and Area 2	0.0707	MW/radian
T_w	Water start time in the hydropower plant in Area 1 and Area 2	1	s
T_1	Governor rest time	5	s
T_2	Transient drop time constant	41.6	s
T_3	Main servomotor time constant	0.513	s
F	System frequency	50	Hz

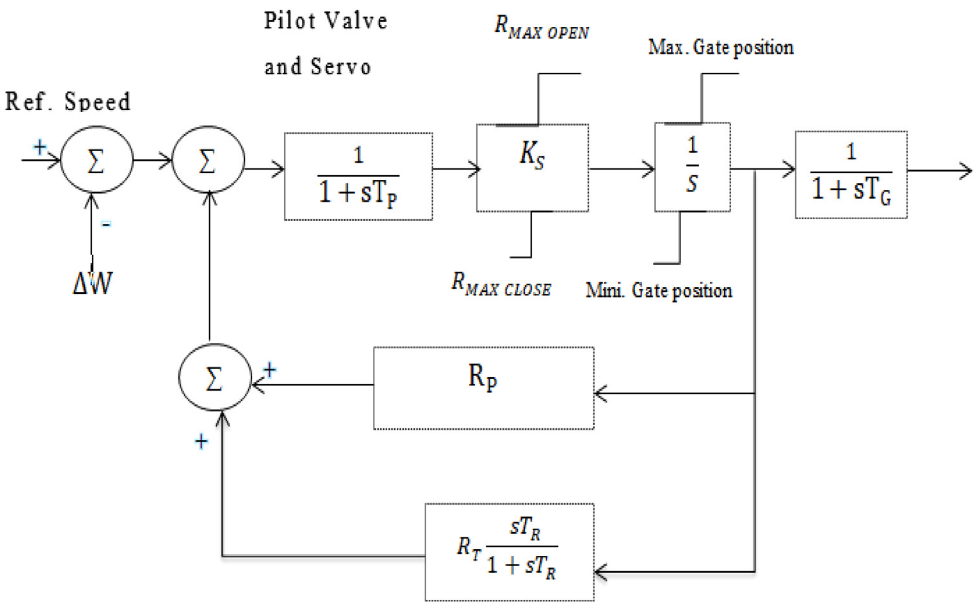

Fig. 1. Block diagram of the hydropower governor.

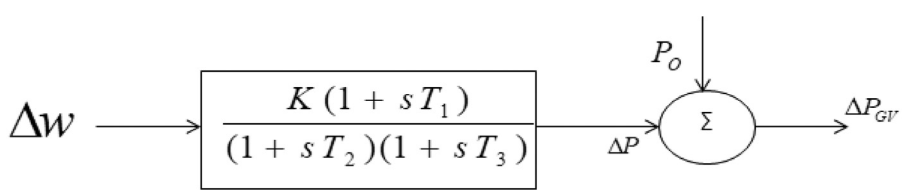

Fig. 2. Block diagram of speed governor.

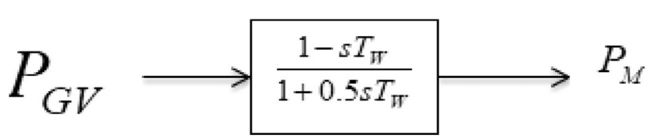

Fig. 3. Transfer function model of the hydro-turbine.

where $e(t) = y_{sp}(t) - y(t)$ is the system error, $u(t)$ is the control variable output, K_p is the proportional gain, K_D is derivative constant, and K_I is integral time constant. In general, the proportional gain improves the settling time, the integrator eliminates the steady state error, and the derivative gain improves the overshoot of the plant which improves the plants performance.

4.1. Fuzzy logic control

The FLC concept employed in this work was adopted from Chan and Shi (2011). One of the most useful application of Fuzzy Logic (FL) is in the design of a controller. Most complex processes are controlled by human operators, but expert systems attempt to capture this operation for effective operation of a system such as a hydropower plant. In addition, FLCs act to imitate human beings thought as well as perception to do specific task which are similar to human daily activities. FLCs consists mainly of four components which are: Fuzzification, decision making unit, inference engine, and Defuzzification (Petković et al., 2021; Nikolić et al., 2016). Membership functions (MFs) of a FLC may have various sizes which are dependent on the designer's interest when designing the FLC for a specific purpose in a control system. The steps to apply a FLC for AGC of a hydropower plant are given as:

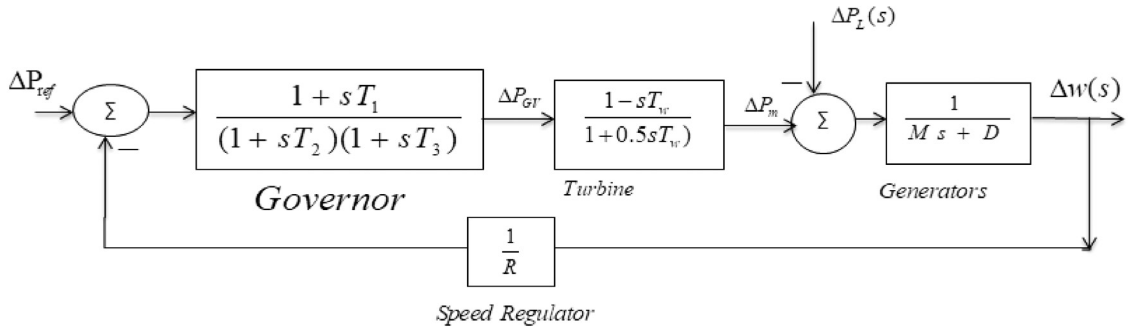

Fig. 4. Single area load frequency control.

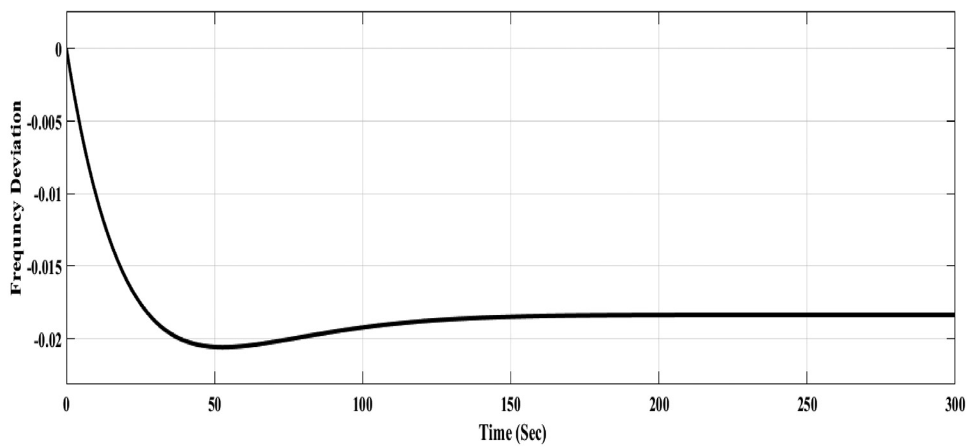

Fig. 5. Frequency response of AGC for a single area.

(i) determine the area control error and change in rotational speed;
(ii) transform the error and rate of change of rotation speed to fuzzy terms; and
(iii) determine and evaluate the rule decision terms which are available in the rule base. This is determined using the compositional rule of inference of a fuzzy system and is used to determine the specified input which is needed to supervise the plants states.

In a two area hydropower plant, the major factors to be considered are area control error (ACE), rate of change of area control error (DACE), and the output which is the control power setting. In this work, 5 × 5 triangular MFs was applied and the Centroid method defuzzification technique was used.

4.2. Adaptive Neuro-Fuzzy Inference system (ANFIS)

Adaptive Neuro-fuzzy inference systems (ANFIS) are FIS which apply the ANN concept to generate fuzzy sets and fuzzy rules by the processing of collected data samples. ANFIS capture the behavior of the input–output acquired data sets in order to correct plant parameter settings. The proposed architecture of the ANFIS is presented in Fig. 7. The square nodes in the architecture structures are represented as a collection of the parameters of the membership functions (MFs) for Takagi–Sugeno–Kang (TSK) inference systems which are adjusted/tuned during the optimization process. However, the circles nodes are not adjustable/tuned and perform activities such as max/min computations.

Where, n-represents normalization, W_1 and W_2- are the weights of the network.

The assumptions made for the ANFIS network architecture in Fig. 7 are listed as follows: has two inputs, X_1 and X_2, and one output (f). Each input is denoted by two fuzzy sets (X_1 has fuzzy set A_1 and A_2, and X_2 has fuzzy sets B_1 and B_2). The result/output is represented by a 1st order polynomial. The ANFIS shown in the Fig. 7 is governed by two rules which are: Sugeno's rule base of the fuzzy inference system. These rules are given as follows:
1st Rule: if X_1 is A_1 AND X_2 is B_1, THEN $f_1 = p_1X_1 + q_1X_2 + r_1$
2nd Rule: if X_1 is A_2 AND X_2 is B_2, THEN $f_2 = p_2X_1 + q_2X_2 + r_2$

In general, for 'i' rule, the above first order polynomial function can be written as:
If X_1 is A_i AND X_2 is $B_{i,}$ THEN $f_i = p_iX_i + q_iX_i + r_{i.}$
where:
X_1 and X_2 are inputs of the fuzzy set.
$A_i$and B_i are fuzzy sets in the universe of discourse of X_1 and X_2, respectively.

Fi- is the output of fuzzy set within the specified areas by the fuzzy rules, and p_i, $q_{i,}$ and r_i, are design parameters which are determined during the training of the ANFIS model. When the ANFIS is used, the Sugeno fuzzy model which has five layers is used for the proposed controller.

Layer 1: the first layer is responsible for the mapping of the input variable relative to each MF. It is also responsible for transferring the external crisp signal directly to the other layers. It contains adaptive nodes that require suitable premise MFs.

Layer 2: this layer is the fuzzification or input membership layer which receive crisp inputs and determines the inputs belonging

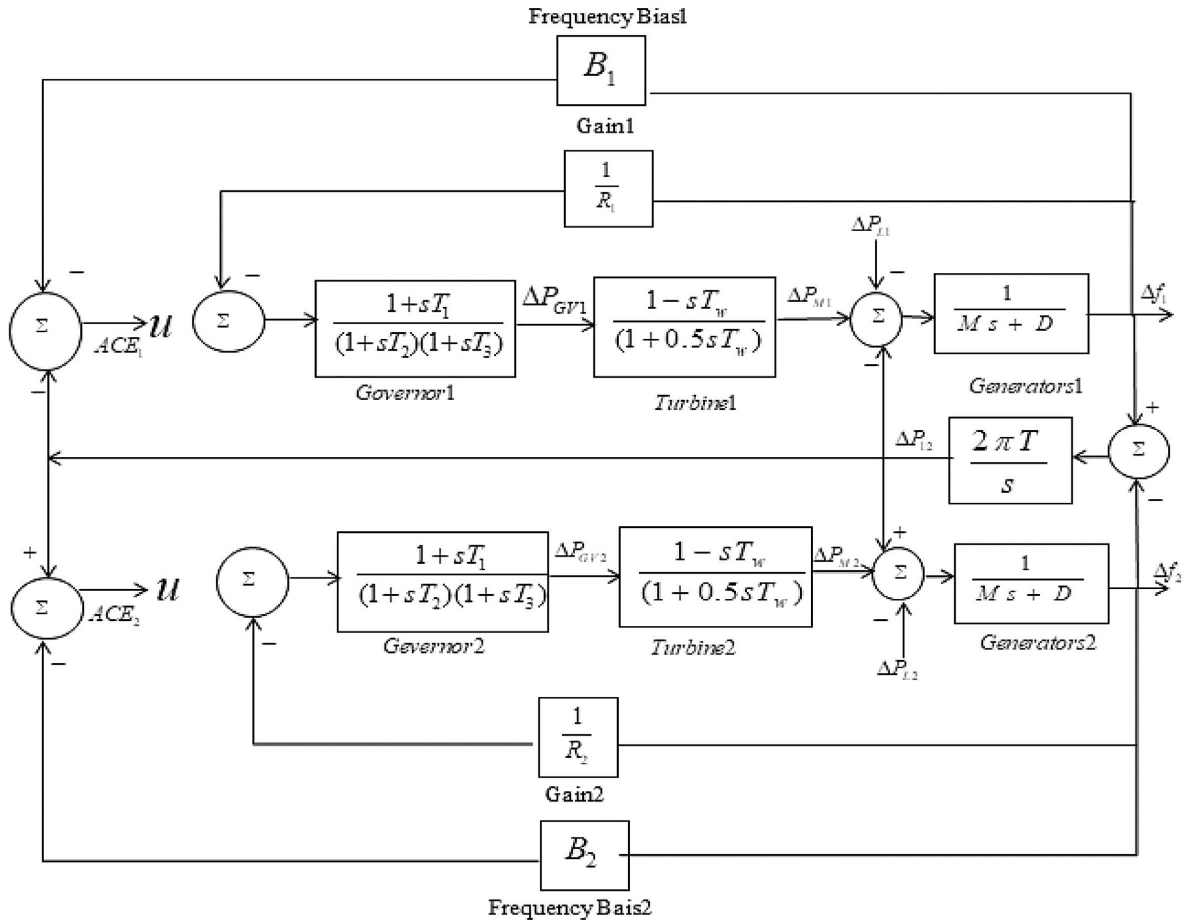

Fig. 6. Block diagram for hydro-hydropower plant.

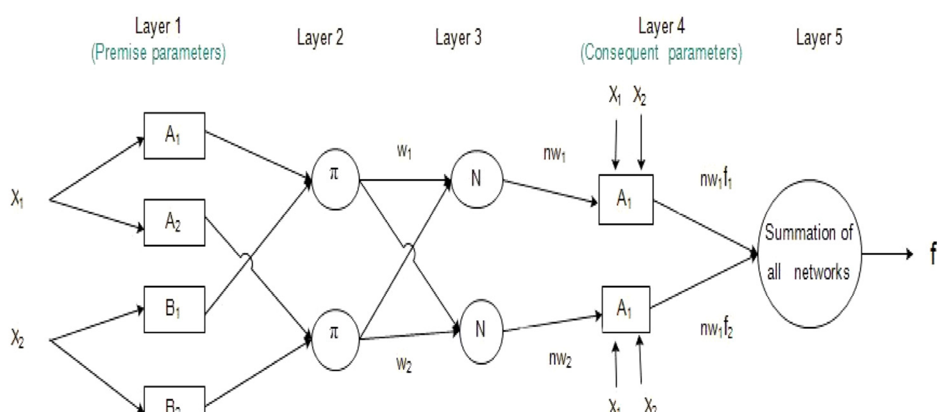

Fig. 7. ANFIS model architecture.

to the neuron 'i' of the fuzzy set. The operator T-norm is applied in this layer to calculate the antecedents of the rules.

Layer 3: the third hidden layer is the fuzzy rule layer. Fuzzy rule neurons receive input from fuzzification layer neurons to represent fuzzy sets in the rule antecedents. It performs the normalization role of layer two (it normalizes the rules strength followed by the fourth hidden layer where consequences of the rules are determined). In a Neuro-Fuzzy system, intersection can be implemented by the product operator.

Layer 4: the fourth layer is a normalization layer. Neurons in this layer denote fuzzy sets used in consequent rules and are used to calculate the normalized firing ability of the given rule. The firing strengths is the ratio of the strength of firing an available rule and the sum of firing strength of the whole rule.

Layer 5: this layer is the defuzzification layer. Neurons of this layer represent a single output of the ANFIS system. It takes the output of the fuzzy set and the respective combined firing strength and integrates them to a single fuzzy set. ANFIS can apply a normal defuzzification technique such as the centroid method. This layer calculates the global output as the summation of all the signals that arrive at this layer. We used the sum–product composition technique. The sum–product composition technique determines the crisps output of the weighted average of the centroid of all output MFs.

The output of ANFIS is determined by applying the consequent variables found in the forward pass. The output of the ANFIS is determined by applying the consequent variables found in the forward pass, and the output deviation learns the variables by using a standard Back propagation algorithm (BPA). In designing the system, we cannot just decide the membership function (MF) to be used just by merely looking at the sets of data. When the ANFIS is used as the controller, the special requirement is that, the MFs parameters should be tuned in a manner to give the best performance of the plant. The adaptive network's output is linear for some of the network's parameters and we can identify these linear parameters by using the LSE method. As a result, this approach leads to the application of a hybrid learning rule which combines both a steepest descent and a least square estimator for fast identification of parameters in the system. The combined learning technique highly supports the plant to speed up variables adaptation. Typically, a least Square sequential is used to obtain a forward pass in order to classify parameters of the consequence, whereas the backward pass is used to establish the premise parameters. The MF may vary based on selection, but most of the time, triangular and bell shaped MFs are used. In this work, generalized bell shaped MF was chosen because of its continuous state, which improves the differential calculations when the Back propagation (BP) algorithm is used. In this work, the frequency error and rate of change of frequency errors are inputs and the command signal is the output in order to model the ANFIS controller.

4.2.1. Procedure to model the ANFIS controller for the AGC system

Area control error and rate of change of area control error are the inputs for the two area system, whereas frequency error and change in frequency error are the inputs for the single area, while the output for both systems is the Power setting control signal. Data was collected from PID controller to provide the required training and testing data for the ANFIS model. Modeling the ANFIS controller involves: generating of the input–output data pair to specify the controller's variable range. Then initialize fuzzy MFs and then tune the MFs using the Neuro-Fuzzy structure. Hybrid learning algorithm which combines both Back propagation algorithm and least square estimation method was the selected optimization technique.

4.2.2. Training of the ANFIS model

The learning algorithm of the ANFIS network is used to adjust the adaptive node parameters (premise and consequent parameters) to achieve the desired performance. The training and testing processes is key stage in ANFIS modeling as it defines the behavior of the developed model. The testing dataset was used to verify the accuracy as well the effectiveness of the ANFIS model. The data used to develop the proposed model of the AGC for hydropower plants is 7013. 78.5% of this data is used for training of the proposed model and 21.5% of the data was used for testing the generalization of the developed model. During the learning phase, the number of epoch was 500. At this point, an acceptable root mean squared error (RMSE) was achieved and as a result the training of the model was stopped.

5. Results and discussion

An isolated and interconnected hydropower plant has been presented in this work. The performance of the AGC of the hydropower plant was tested with PID, FLC, and Adaptive Neuro-Fuzzy inference system (ANFIS) controllers. For both the self-supporting as well as interconnected Hydro-Hydropower plant, the simulations were performed using MATLAB software. The response frequency of the single area power plant with AGC is shown in Fig. 8. The results show an increased frequency deviation with decreased performance of the AGC leading to a very large steady state error. The acceptable tolerance of frequency deviation of the power plant occurs when the deviation is between $\pm1\%$. The error in frequency obtained for the single area hydropower plant with AGC action is 0.023 p.u., while the actual frequency is 1.15 Hz deviated from the normal. If this operating condition is allowed to continue, it will not only affect performance, but will lead to damage of system components. To solve this challenge and to generate a stable power supply, other controllers such as PID, FLC, and ANFIS were also used. The response of the AGC with the PID controller was improved compared to that of when the AGC was used only. The application of AGC with the PID controller achieved a settling time of 90.542 s, an overshoot of 24.375%, and frequency error of 0.0052 p.u. The performance of AGC of the hydropower plant in the single area with FLC achieved a settling time of 48.465 s, overshoot of 13.065%, and a frequency deviation of 0.0032 p.u. The results show that the FLC is stable with the application of AGC compared to that of AGC with the PID controller.

It was observed that the AGC without applying a controller gives an increase in frequency deviation of about 1.15 Hz. This frequency deviation is far from the standard operating range; such operating range of frequency with the application of AGC not only affects performance of the hydropower plant, but is also harmful to components of the system. The response of the AGC with the Adaptive neuro-fuzzy system (ANFIS) controller is shown in Fig. 9. The results in Fig. 9 show an improvement in the frequency response compared to that of the proportional–integral–derivative (PID) control and fuzzy logic control (FLC).

The ANFIS controller takes advantage of both controllers; the FLC which has the ability to cater for human imitate knowledge representation and explanations, and the ANN controller which is capable of performing parallel computations of learning. The application of AGC with ANFIS gives a better performance when compared to other controllers in the single hydropower plant. The settling time, peak overshoot, and frequency deviation of the AGC with Adaptive Neuro-Fuzzy Inference system (ANFIS) controller in single area hydropower plant are 11.616 s, 1.531%, and 0.0014 p.u., respectively.

In a two area hydropower plant, unlike the single area hydropower plant, controlling the range of the scheduled frequency is a challenge. However, besides maintaining a nominal operating range of frequency in the two area hydropower plant, the Tie line power flow deviation should be supervised based on predetermined values. Even though interconnected power plants maintain a certain level of power quality, the control mechanism is still a challenge due to their nonlinear and time varying behavior. This situation in two area hydropower plants require fast switching control action to regulate the disturbed system. Dynamic oscillations, frequency deviation, and steady state errors were found to be high in both Area 1 and Area 2 with the application of AGC. The simulation results of the Hydro-hydropower plant with the application of AGC in Area 1, Area 2 are shown in Figs. 10, and 11, while that of the tie line power flow deviation is shown in Fig. 12.

When AGC is applied, it maintains an actual frequency value of about 48.7 Hz. The frequency deviation is very large relative to its operating value of 1.3 Hz, while per unit deviation, the frequency deviation is 0.026 p.u. This is not an acceptable frequency error because in an interconnected hydropower plant, the frequency deviation is expected to be very small, even when the plant has other renewable energy sources such as wind power plants which also contribute to the high fluctuation which occur in the plant. In this case, a fast and high performance controller is required

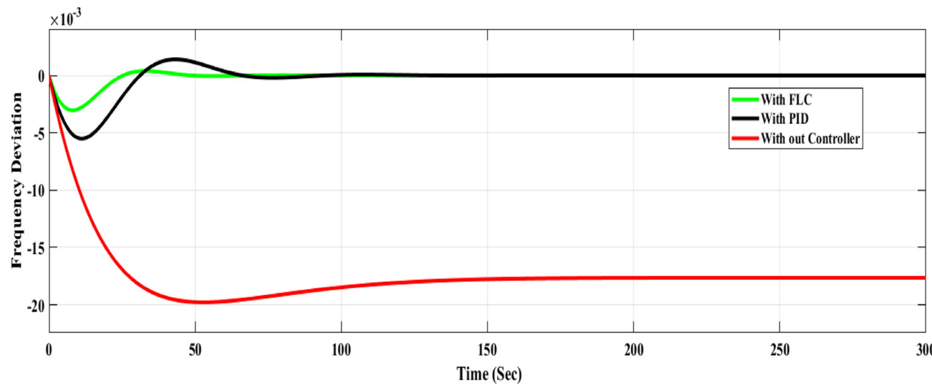

Fig. 8. Response of AGC with PID and FLC.

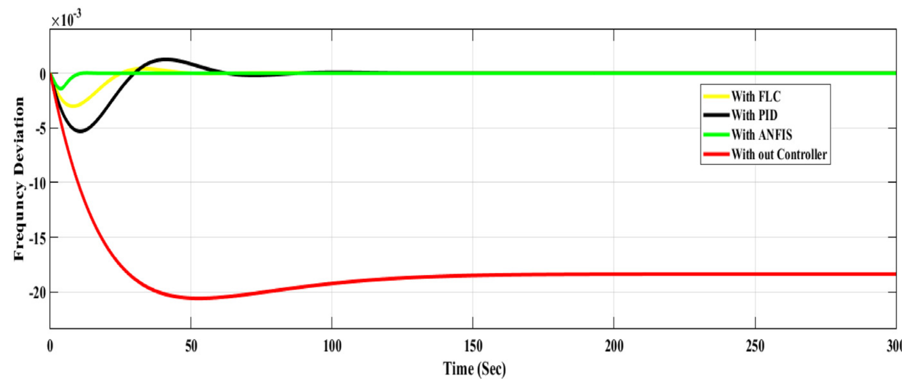

Fig. 9. AGC with PID, FLC, ANFIS in single area.

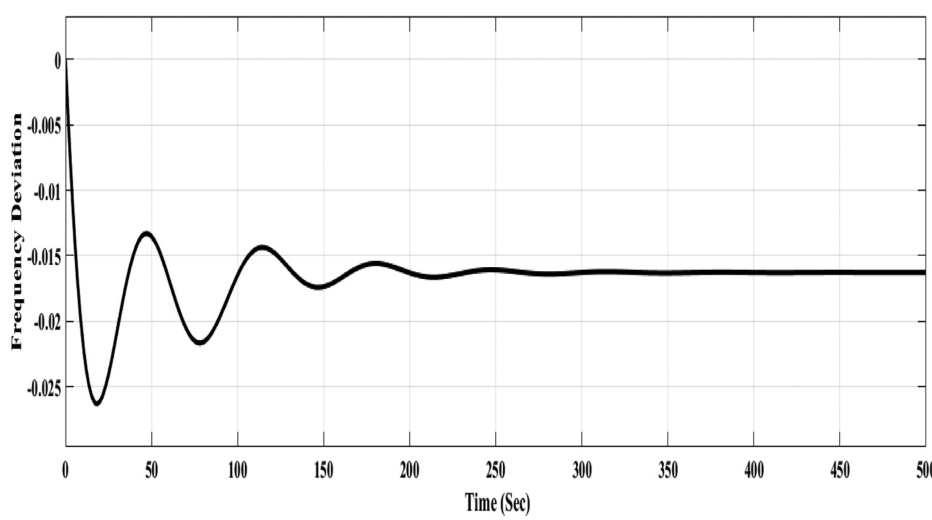

Fig. 10. Response AGC action only in Area 1.

such as the ANFIS controller. The application of the AGC only was not able to deliver the required performance because it needed further improvement in its frequency and tie line power flow as shown in Fig. 12. The dynamic oscillation, frequency deviation, settling time, and overshoot are improved in the case of the application of AGC with the PID controller compared to when the AGC is applied alone as shown in Fig. 13, while the performance slightly decreases when AGC with FLC is used as shown in Fig. 14. In the hydropower plant, the application of AGC with PID control gave a settling time, overshoot, and frequency deviation of 130.79 s, 32.221%, and 0.00591 p.u., respectively as shown in Fig. 15. The performance of AGC with PID control gives better results compared to when AGC is applied only as shown in Fig. 12.

The dynamic oscillation, frequency deviation as well as settling time of the hydropower plant was improved with the application of AGC with FLC compared to that of AGC with the PID controller. The overshoot, settling time, and frequency deviation obtained with the application of AGC with FLC control are 24.375%, 71.662s, and 0.0022 p.u., respectively as shown in Fig. 16. The response of AGC in Area l and Area 2 with PID, FLC and ANFIS are shown in Figs. 17 and 18. A better performance was obtained

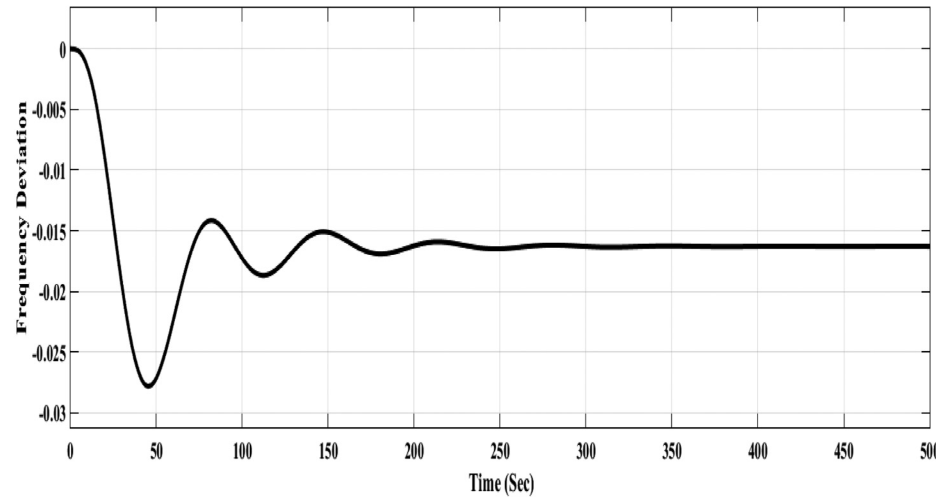

Fig. 11. Response of AGC action only in Area 2.

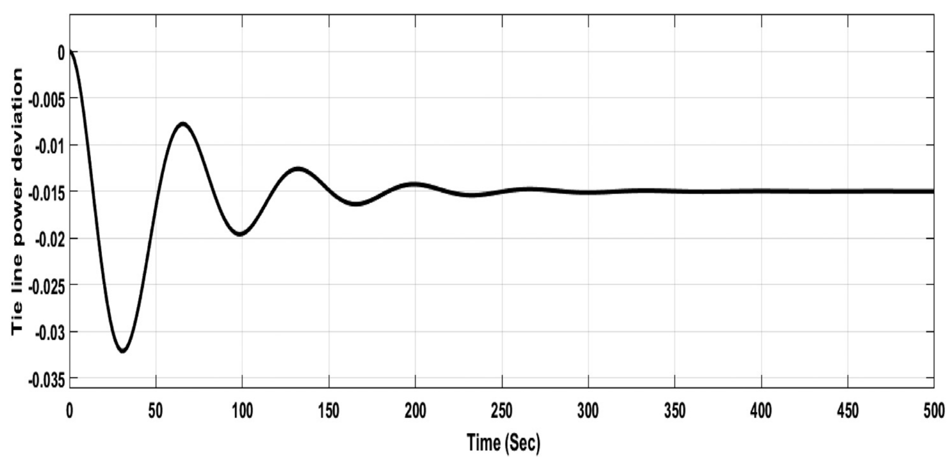

Fig. 12. Tie line power flow deviation in AGC only.

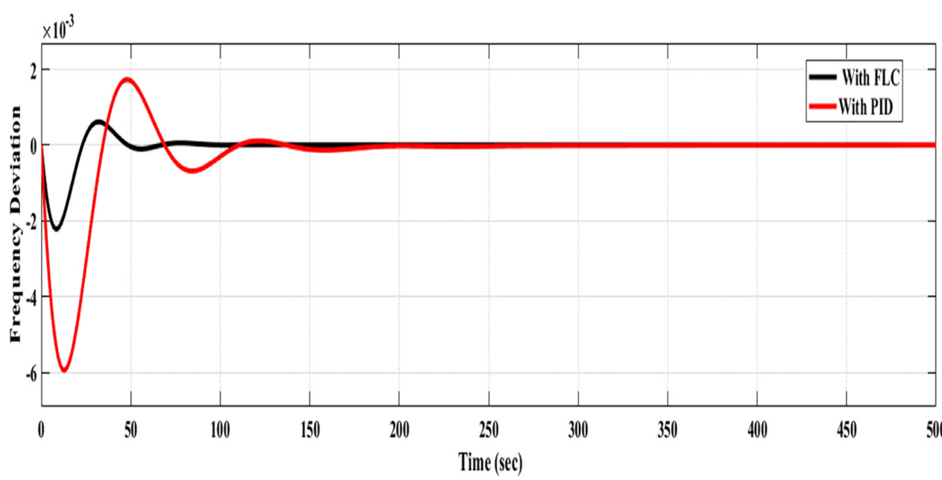

Fig. 13. Responses of AGC with PID and FLC in Area 1.

with the introduction of PID in Area 1 as shown in Fig. 17, while the introduction of ANFIS gave better results in Area 2 as shown in Fig. 18. The introduction of ANFIS gave an overshoot, settling time, and frequency deviation of 17.059%, 28.904 s, and 0.0016 p.u, respectively as shown in Fig. 19. The FLC depends on the expert system in order to study and control the system. However, the use of the ANFIS made the fuzzy inference system (FIS) to depend less on the expert system. In addition, MFs is reduced from 5 to 3, which indicates a reduced memory size and overall cost reduction.

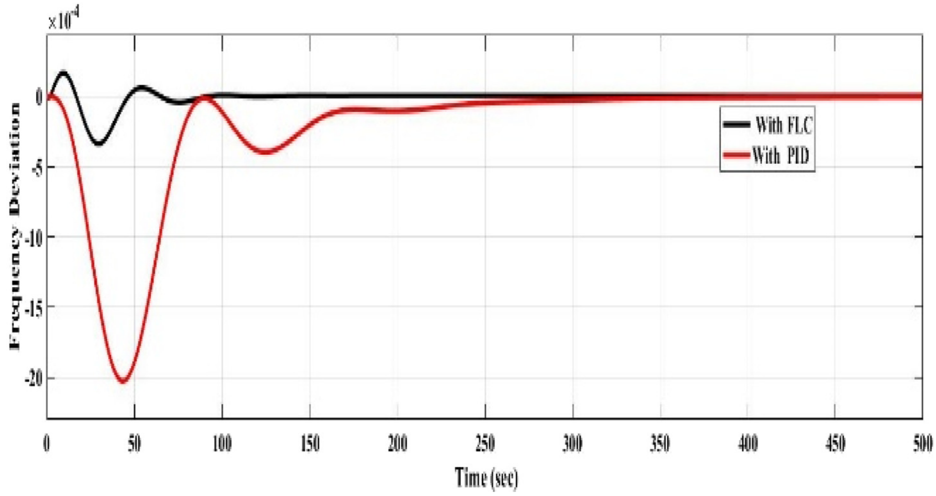

Fig. 14. Responses of AGC with PID, and FLC in Area 2.

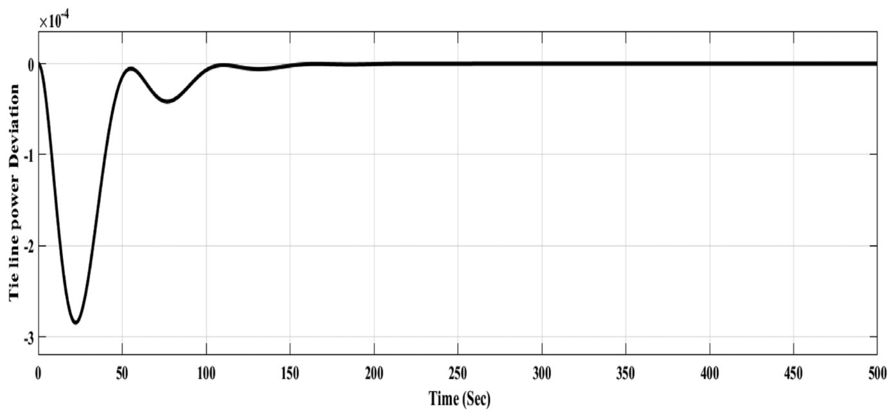

Fig. 15. Tie line power deviation of AGC with PID.

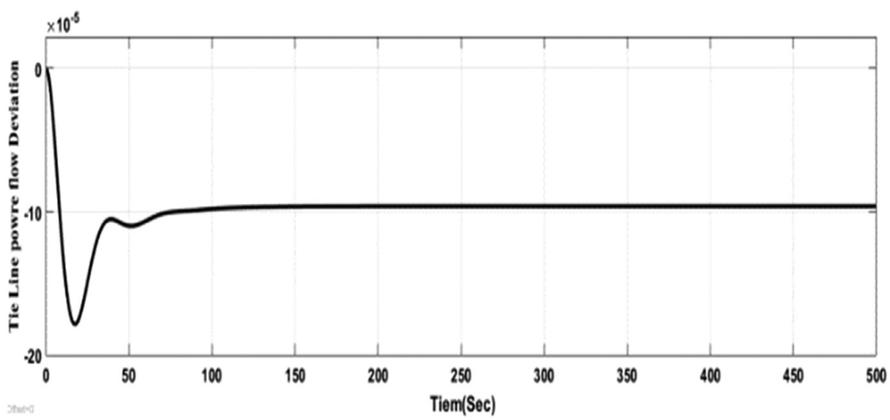

Fig. 16. Tie line power flow deviation AGC with FLC.

6. Conclusion

In this paper, the modeling of an Automatic Generation Control (AGC) for a hydropower plant was presented. Comparative analysis was performed using different controllers such as PID, FLC, and Adaptive-Neuro-Fuzzy Inference system (ANFIS) to determine the most suitable controller. The comparison study was performed using MATLAB software to test the performance of the controllers. The performance of each controller was investigated with AGC based on the step load disturbance of a two area as well as single area hydropower plant. The behavior of the actual frequency and tie line power flow was also studied. The simulation results of the different controllers was obtained for the step load disturbance of the hydropower plant. The proposed ANFIS controller reduced the frequency deviations and made the system return to its normal operation faster compared to when the other controllers were used. The frequency deviation obtained appears small, but in real power systems such deviations drastically reduce the quality of the power supply especially for interconnected systems. In general, the results show that

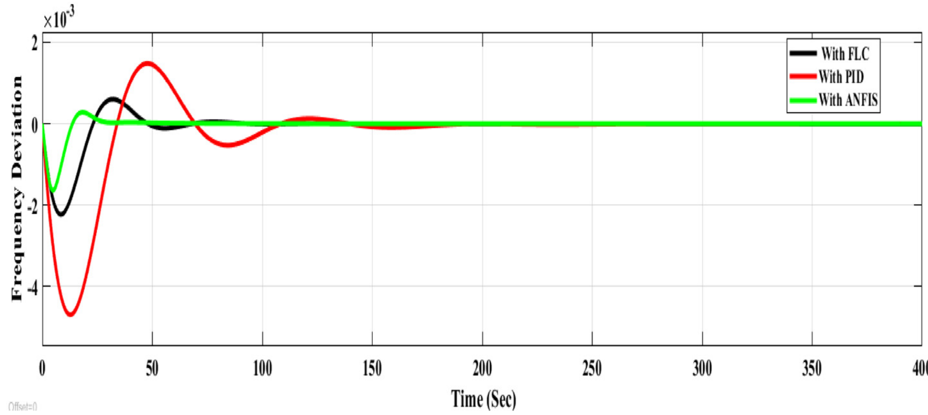

Fig. 17. Response of AGC in Area I with PID, FLC and ANFIS.

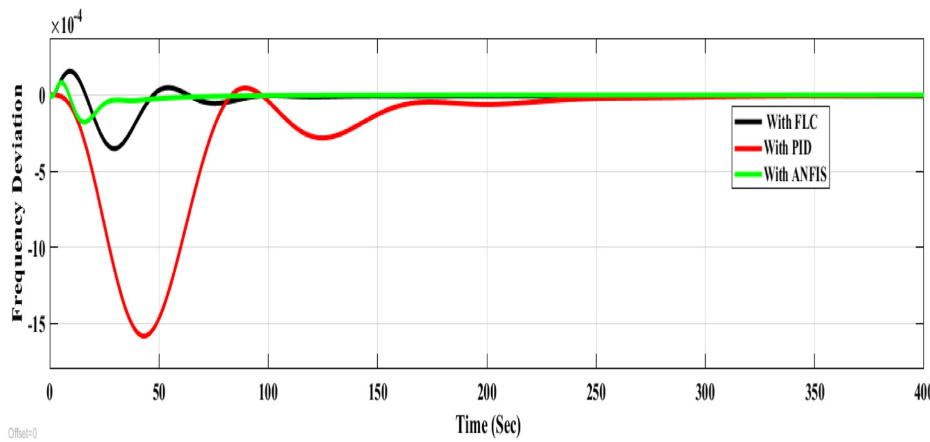

Fig. 18. Response of AGC in Area 2 with PID, FLC and ANFIS.

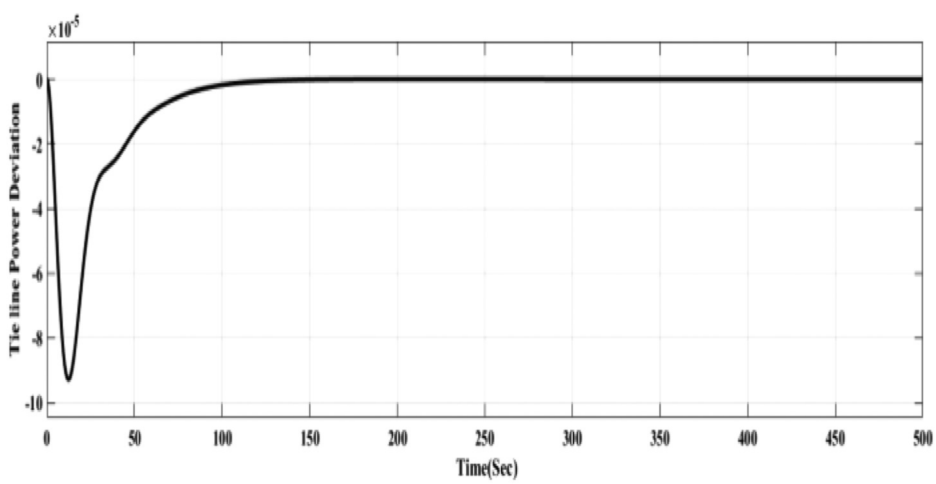

Fig. 19. Tie line power Deviation with ANFIS.

the ANFIS achieved a superior performance compared to other controllers. Therefore, we can conclude that the ANFIS controller is better compared to the FLC and PID controllers. The load frequency control was only introduced for small perturbation, but in future works, authors hope to compare the performance of the AGCs and automatic voltage regulators (AVR), since their frequency and voltage can be decoupled and studied for very small perturbation.

CRediT authorship contribution statement

Tilahun Weldcherkos: Conceptualization, Investigation, Methodology, Software, Writing – original draft. **Ayodeji Olalekan Salau:** Data curation, Investigation, Methodology, Writing – review & editing, Validation. **Aderajew Ashagrie:** Investigation, Visualization, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability statement

The authors declare that all data presented in this work was generated during the course of the work and any other source has been appropriately reference within the manuscript.

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