American Journal of Applied Sciences 11 (9): 1659-1670, 2014
ISSN: 1546-9239

doi:10.3844/ajassp.2014.1659.1670 Published Online 11 (9) 2014 (http://www.thescipub.com/ajas.toc)

NEURAL CASCADED WITH FUZZY SCHEME FOR CONTROL OF A HYDROELECTRIC POWER PLANT

[1]Selwin Mich Priyadharson, A., [2]T. Ramesh Kumar, [3]M.S. Saravanan, [4]C. ThilipKumar and [5]D. Dileepan

[1,4,5]School of Electrical,
Vel Tech Rangarajan Dr. Sagunthala R and D Institute of Science and Technology, Chennai, India
[2]EEE Department, Vel Tech High Tech Engineering College, Chennai, India
[3]Department of CSE, Saveetha School of Engineering, Saveetha University, Chennai, India

Received 2014-06-15; Revised 2014-07-14; Accepted 2014-08-25

ABSTRACT

A novel design for flow and level control in a hydroelectric power plant using Programmable Logic Controller (PLC)-Human Machine Interface (HMI) and neural cascaded with fuzzy scheme is proposed. This project will focus on design and development of flow and level controller for small scale hydro generating units by implementing gate control based on PLC-HMI with the proposed scheme. The existing control schemes have so many difficulties to manage intrinsic time delay, nonlinearity due to uncertainty of the process and frequent load changes. This study presents the design of neuro controllers to regulate level, cascaded with fuzzy controller to control flow in gate valve to the turbine. A prototype model is fabricated in the laboratory as experimental setup for flow and level control and real time simulation studies were carried out using PID and neural cascaded with fuzzy scheme. The designed prototype model is fabricated with 5 levels in the upper tank and 2 levels in the lower tank. Based on the outputs of the level sensors from the upper and lower tanks, the ladder logic is actuated. This project work uses PLC of Bernecker and Rainer (B and R) Industrial Automation inbuilt with 20 digital inputs and provides 12 potential free outputs to control the miniaturized process depicted in this work. Finally, the performance of the proposed neural cascaded with fuzzy scheme is evaluated by simulation results by comparing with conventional controllers output using real time data obtained from the hydro power plant. The advantages of the proposed neural cascaded with fuzzy scheme over the existing controllers are highlighted.

Keywords: Hydropower Plant, Back Propagation Neural Network, FLC, PLC-HMI

1. INTRODUCTION

Amoung the various Renewable energy sources, hydro electric power is the mainly used renewable energy sources for power generation. In hydro power plant, water potential energy is transformed into electric energy. The hydro power generation is anchored in the accessible water flow and altitude it plummets (Rajeswari *et al*., 2012).

Electricity demand will not be steady at all times. In order to manage the high load demand, pumped storage is preferable. Pumped storage is maintaining water in reserve for high load demand by pumping water that has previously flow through the turbines. Because of this pumped storage method of reusing the water more than once, hydroelectric power plants is the efficient source during high load than other power plants.

And also to give solutions to the demerits of conventional type such as Ecosystem damage, siltation, flow shortage, methane emissions etc., automation can be used (Guo, 2009). Rajeswari *et al*. (2012) emphasized on controlling the process variables level

Corresponding Author: Selwin Mich Priyadharson, A., School of Electrical,
Vel Tech Rangarajan Dr. Sagunthala R and D Institute of Science and Technology, Chennai, India

and flow with real time implementation of gate control in hydro power plant using PLC. Liang (2000) proposed a neural network approach for the hydroelectric generation setting up with pumped-storage units. King *et al*. (2001) discussed the development of a Fuzzy Inference System (FIS) based governor control for a pumped storage hydro power plant. Stokelj *et al*. (2000) described neural networks for water inflow into the head of the hydro power plant reservoir. Isasi-Viñuela *et al*. (1997) introduced a Neural Network (NN) module for matching with various circumstances of the plant (Karthigayani and Sridhar, 2014). Molina *et al*. (2000) introduced architecture, NN Acoustic Prediction (AP) and NN Predictive Maintenance (PM) for managing hydro power plants. Jasa *et al*. (2012) constructed neural network-based PID control to control the governor so as to standardize the quantity of water running into turbine. Goyal (2006) proposed a flow control based model for the automatic control of small hydro power plants and performed parameter optimization using Artificial Neural Networks.

Singh and Chauhan (2011) described that an exact signal is necessary to manipulate the gate that has to be identified and it will match the requirement of sudden large change in the loads. Also he described that the maximum sudden increase and decrease in load system has to be expected and consequent manipulation in gate position has to be well-known.

With the target of enhancement in the performances of hydro power plant, the Neuro level cascaded with Fuzzy flow scheme based on PLC-HMI is proposed. The present paper is structured as follows: Section 2 deals with hydro power plant and prototype model. Section 3 deals with the conventional scheme for hydroelectric power plant. Section 4 describes Neuro level cascaded with fuzzy flow scheme for control of hydro power plant. Section 5 describes the PLC-HMI. Section 6 describes the simulation studies. Section 7 gives the summary and conclusions.

2. HYDRO POWER PLANT AND PROTOTYPE MODEL

The Lab scale Experimental Set up operation is shown in **Fig. 1**. It is provided with lower tank of two levels and upper tank of five levels (Rajeswari *et al*., 2012). The upper five levels are Low level, Average level, Medium level, High level and Danger level. Where as the two levels of the lower tank are Low level and High level.

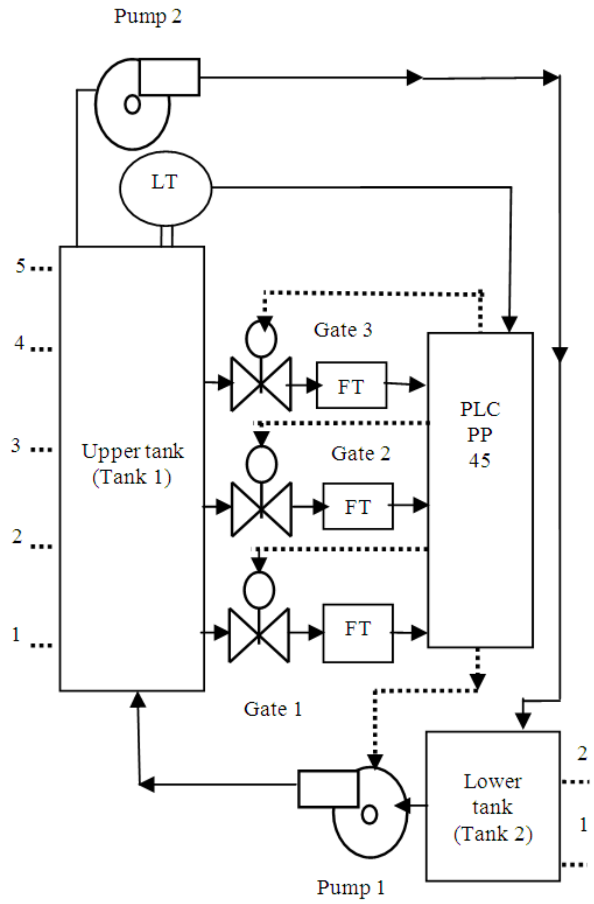

Fig. 1. Operation of prototype model

The Block diagram of Hardware set up is shown in **Fig. 2** which consists of the hardware components Programmable Logic Controller, FT-Flow transmitters, LT-Capacitive level transmitter, Pumps and Valves. The sequences followed in hydro power plant that is put into operation in the prototype model (Priyadharson *et al*., 2014) are illustrated as follows.

When the water level in the lower tank reaches the low level, the pump 1 is actuated and the water is taken to the upper tank from the lower tank. In upper tank when the water level reaches the low level pump 1 is again switched on and water level raises upto average level. When water exceeding average level, Gate 1 is allowed to open.

Similarly when the level attains medium level, the pump 1 actuated and the water raises upto high level. When water is mounting beyond medium level, Gate 1 and 2 is opened and when water level is exceeding beyond high level, Gate 1, 2 and 3 is opened. When the level increases beyond the high level, the pump 2 is actuated and water is taken back to lower tank. If the water level reaches high level in lower tank, Gate 1, Gate 2 and Gate 3 will be closed and also the pumps 1 and 2 will be switched off. Based on the Level Transmitter (LT) output the ladder logic is programmed and as per the programmed ladder logic, the pumps and also the opening of gates of the dam are actuated at their respective levels.

The Lab scale experimental set up is operated based on the sequences demonstrated. The lab scale experimental set up is shown in **Fig. 3**.

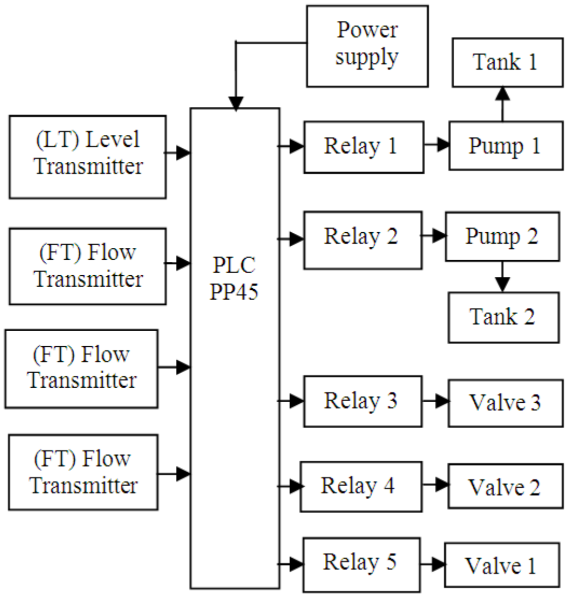

Fig. 2. Block diagram of hardware set up

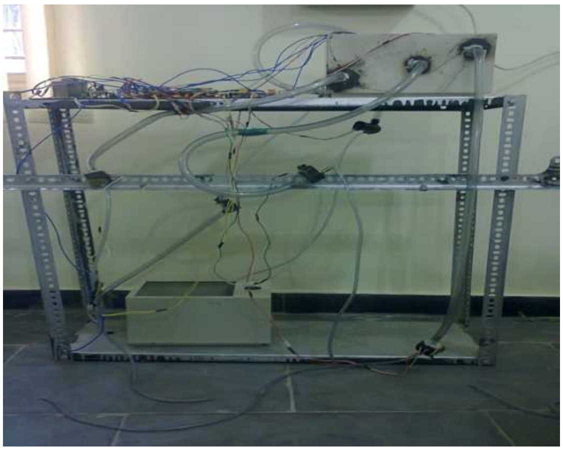

Fig. 3. Lab scale experimental set up

3. CONVENTIONAL SCHEME FOR HYDROELECTRIC POWER PLANT

Figure 4 represents the B and R Industrial Automation PLC, X 20 standard CPU. Using this PLC-X 20 standard CPU, the control action is performed for maintaining the level in the tank and flow rate to the turbine based on load demand.

PLC-X 20 module is shown in the **Fig. 5** in which the Analog Input, Output, Transmitter, Digital Input and Output such as X20AIXXXX, X20AOXXXX, X20ATXXXX, X20DIXXXX, X20DOXXXX etc can be connected to the X20 Module.

Similarly X20CSXXXX-complex module, is used to remotely connect, the complex devices RS232/RS485/RS422/CAN to X20 system. The bus transmitter X20BT9XXX and bus receiver X20BR9XXX is used to connect the X20 system to the X2X link. The stations can be up to 100 m away from each other. Power supply, X20PSXXXX, 24 V DC supply module is used for internal I/O and X2X Link supply. The overall B and R Hardware with Power supply, PLC, Input/Output modules is shown in the **Fig. 6**.

The Hardware components of B and R PLC system is shown in **Fig. 7**. It has:

- Processor Unit (CPU)
- Memory section
- Input/output sections
- Power supply unit
- Programming device
- System buses

In **Fig. 8** Block diagram for flow control in Hydro power plant is represented. Gates (Final Control Element) will open/close in the plant depending on the water level in the reservoir.

The water level in the reservoir is measured by capacitive level sensor. The actual level value is manipulated to the flow set point by using flow manipulator. Comparison between water flow set point and actual flow is done and the error is controlled by PLC which gives manipulated variable to the Gate valves. The water outflow from the gate valve is taken to the turbine.

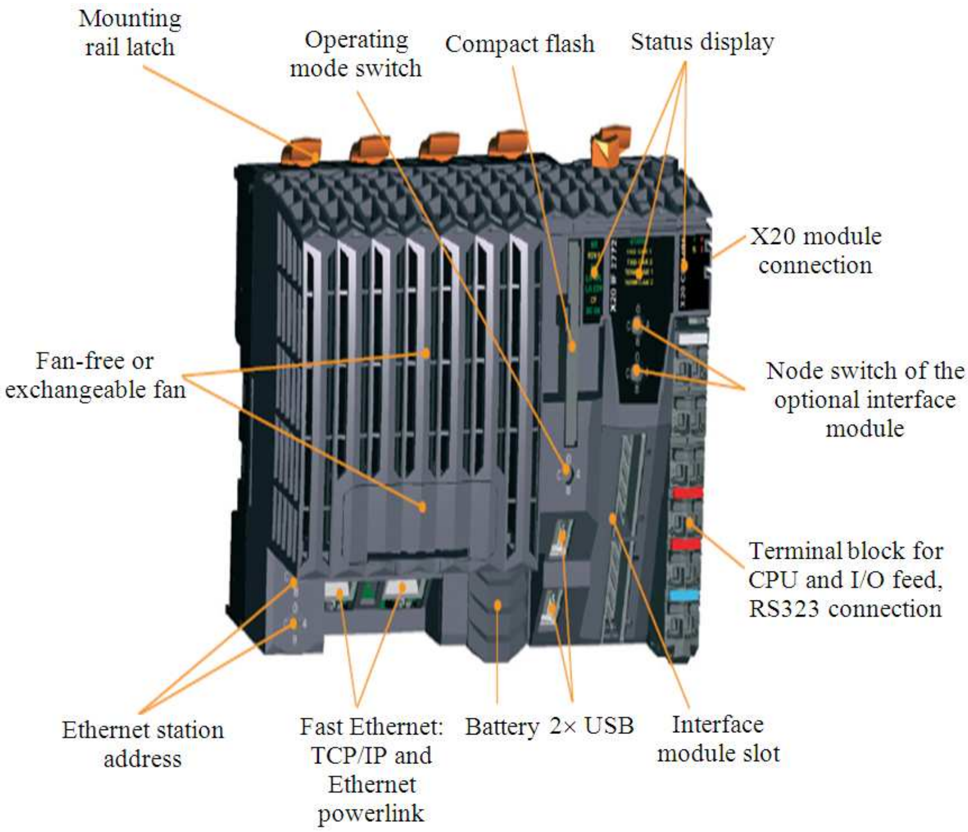

Fig. 4. B and R PLC-X 20 standard CPU

Fig. 5. B and R PLC-X 20 Module

Fig. 6. B and R PLC set up

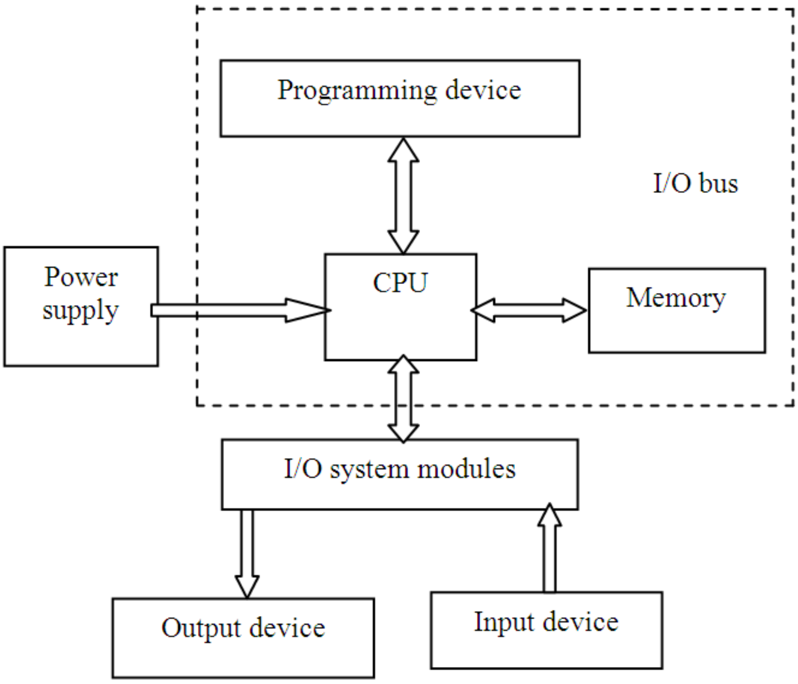

Fig. 7. Hardware components of B and R PLC

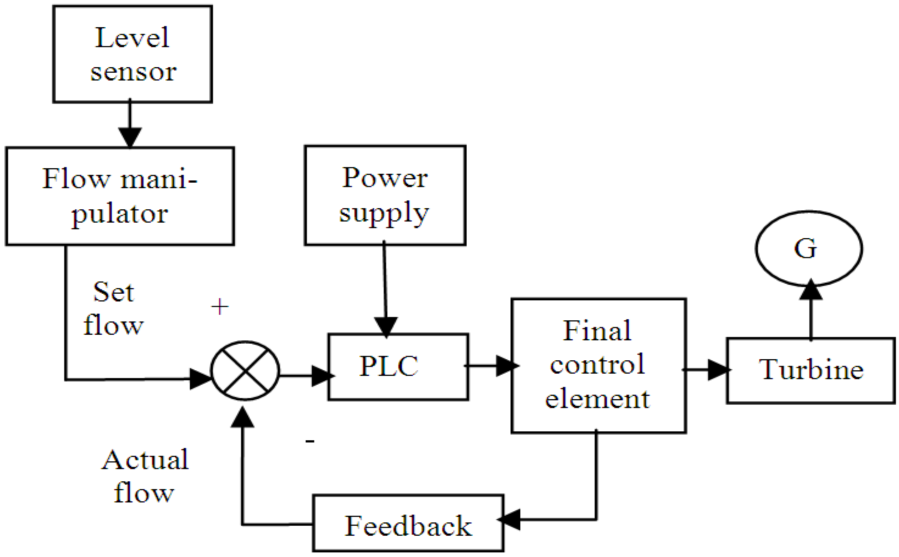

Fig. 8. Block diagram for flow control in hydro plant

4. NEURO LEVEL CASCADED WITH FUZZY FLOW SCHEME FOR CONTROL OF HYDRO POWER PLANT

The block diagram of Neuro level cascaded with Fuzzy flow scheme for Flow and Level control is shown in **Fig. 9**. The difference between the set point and the actual level in the tank is computed as error signal. The error and change in error are taken as inputs to the neuro level controller in **Fig. 10**. In **Fig. 9** the processed signal from level control is applied to maintain effective pump speed. Same signal is applied to a function generator, which generates a set point for the water flow loop with respect to the level in the tank.

The set point for the water flow from the gate valve is derived from water level in the upper tank is referred as cascaded scheme. In generalized cascade controllers, the dynamics of the secondary controller are much faster than those of primary loop. However, for the proposed process, both the loops are considered as primary loops.

The difference between the set point derived from upper tank water level through function generator and the actual flow from the gate valve is computed as error signal. The error and change in error are taken as inputs to the proposed fuzzy controller for flow. The processed signal from the fuzzy controller is applied to the gate valve to maintain flow for proper matching of the load demand.

The neural network architecture is made of one input layer with two neurons, two hidden layers with seven neurons and an output layer with one neuron. The inputs are error and delta error and the output being the manipulated variable. The data for the training of the neural network is obtained from the conventional control. After the weights had been stabilized in the training process the weights are used in the actual process to determine the valve position for the given instantaneous values of error and change in error. The manipulated variable is then transmitted to the gate valve.

Neuro controller to control tank level is shown in **Fig. 10**. The inputs are fed into the input layer and get multiplied by interconnection weights as they are passed from the input layer to the first hidden layer. Within the first hidden layer, they get summed then processed by a nonlinear function. As the processed data leaves the first hidden layer, again it gets multiplied by interconnection weights, then summed and processed by the second hidden layer. Finally the data is multiplied by interconnection weights then processed one last time within the output layer to produce the neural network output.

The neural network learns using an algorithm called back propagation. With back propagation, the input data is repeatedly presented to the neural network. With each presentation the output of the neural network is compared to the desired output and an error is computed.

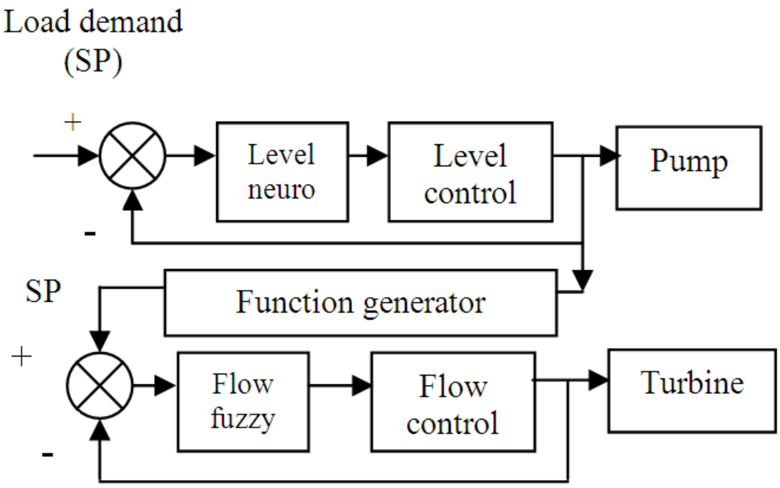

Fig. 9. Block diagram of neuro level cascaded with fuzzy flow scheme

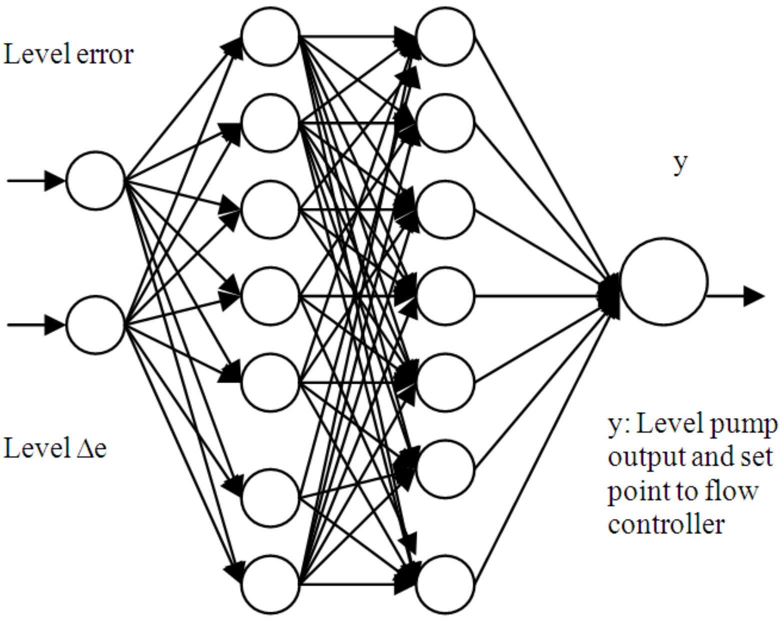

Fig. 10. Neuro controller for tank level

This error is then fed back (back propagated) to the neural network and used to adjust the weights such that the error decreases with each iteration and the neural model gets closer and closer to produce the desired output. This process is known as "training".

The fuzzy controller for air for which the set value is derived from neuro fuel is shown in **Fig. 11**.

The fuzzy logic controller to control the water flow to the turbine has two inputs and one output. The inputs are error and change in error and the output is the controlled output.

The universes of discourse of the input variables are E and ΔE and output variable is U. The following are the range of database considered.

Error (E) for water flow = -20 to +20%
ΔError (ΔE) for water flow = -15 to +15%,
Gate valve Position for water flow (ΔU_A) = 20 to 100%

The number of linguistic terms for each linguistic variable is 5, Error (E) is {MN, N, Z, P, MP}, Change in error (ΔE) is {VS, S, M, L, VL} and Control valve position is {VS, S, M, L, VL} respectively.

The triangular membership functions are used to represent the linguistic terms. A scale mapping is performed using triangular membership function, which transfers the range of input variables into corresponding universe of discourse. An element of each term set is mapped on the domain of corresponding linguistic variable.

Knowledge base consists of database and rule base. Database provides necessary definitions, which are used to define linguistics control rules. In the present work 21 rules for flow are framed while designing FLC scheme. All the rules are represented in the form of rule matrix as presented in **Fig. 12.** The values inside the rule base matrix correspond to gate valve position.

Knowledge to perform deductive reasoning is called inference. Inference mechanism is to draw conclusion from rule base, which can produce an output from a collection of *if-then* rules. In the present work the inference mechanism is designed using Mamdani (min-max) method.

Defuzzification is the conversion of a fuzzy quantity to a precise quantity. In the present work Centroid method of defuzzification method is used:

$$\text{Crisp output } Z^* = \sum_{j=1}^{n} \mu_Z(W_j)(W_j) / \sum \mu_Z(W_j)$$

Where:
J = 1 to N, the number of quantization levels.
$\mu_Z(W_j)$ = Maximum value of membership function corresponding to J^{th} quantization level.
W_j = Value at which membership function reaches maximum value $\mu_Z(W_j)$

5. PLC-HMI

In PLC-HMI, visualization is done to design the process that will be user friendly and also useful to follow the ongoing process online by monitoring in the screen. With the advancement in touch screen, the inputs can be fed in the PLC and if there any changes in the data are that can also be updated online. The B and R PLC-HMI is shown in **Fig. 13**.

Figure 14 indicates the prototype model of the hydro power plant. **Figure 15** indicates the start/stop button in HMI for the designed hyro power plant model. The process can be easily start/stop by just pressing the start/stop button THERE are 3 valves and 2 pumps **Fig. 16** indicates the operation of valves and pumps in specific manner. Visualization is done by using the B and R Automation studio software given by B and R Industrial Automation Pvt. Ltd (Austria).

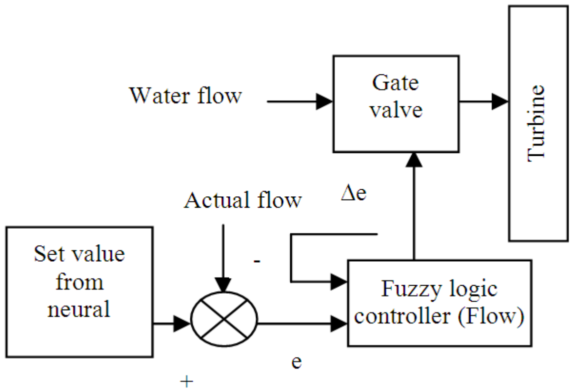

Fig. 11. Neural set value based fuzzy controller for water flow to the turbine

Change in error

Error	VS	S	M	L	VL
MN	-	VS	VS	S	M
N	-	VS	S	S	M
Z	-	-	S	M	L
P	VS	VS	S	M	VL
MP	S	S	M	L	VL

Fig. 12. Rule base matrix

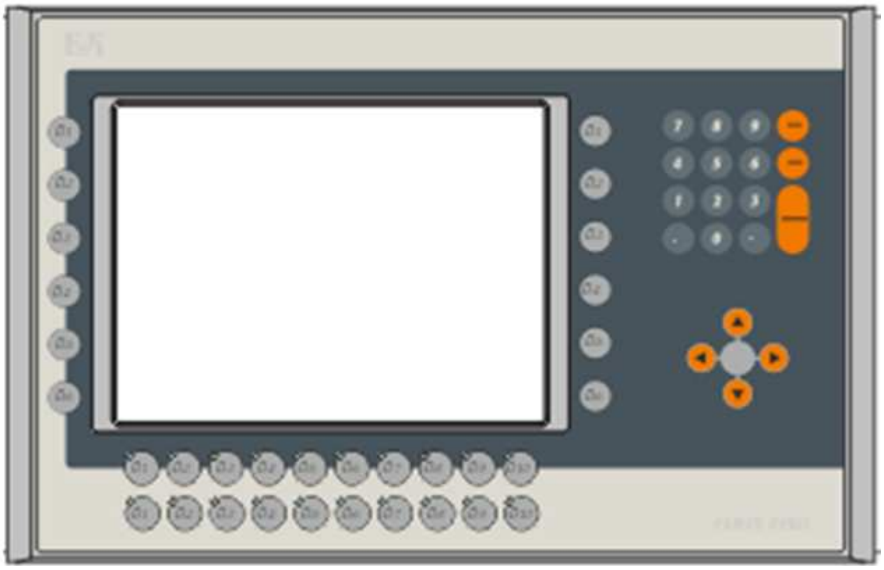

Fig. 13. B and R PLC-HMI

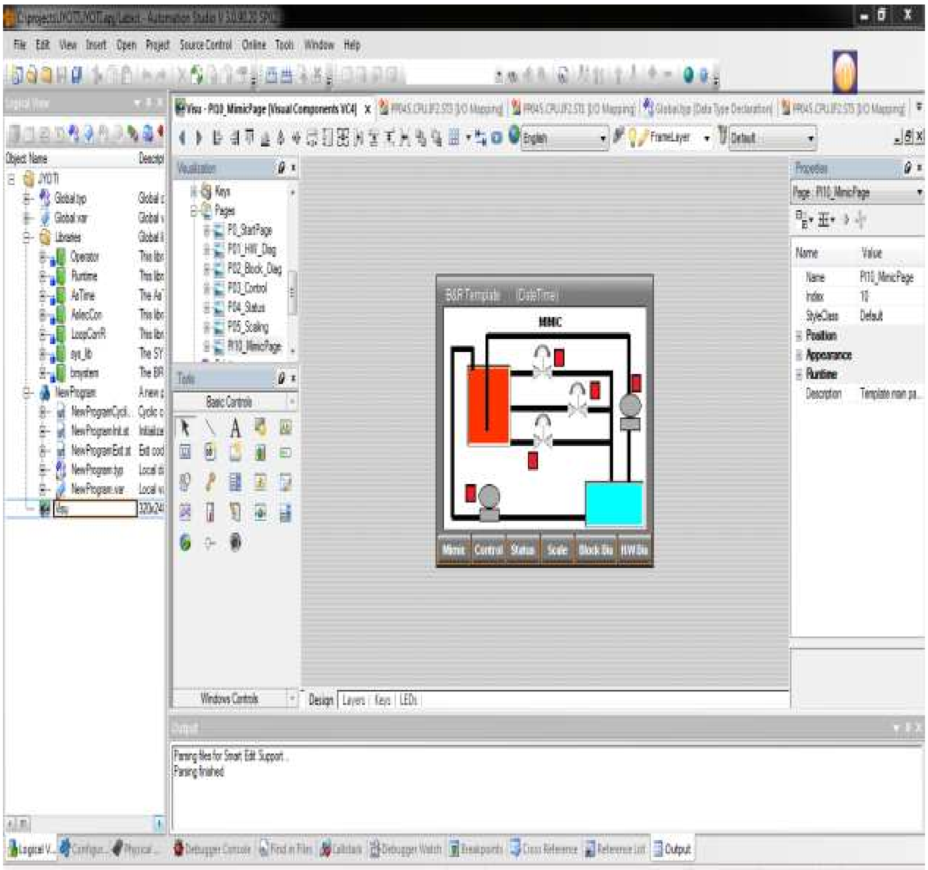

Fig. 14. Prototype model in PLC-HMI

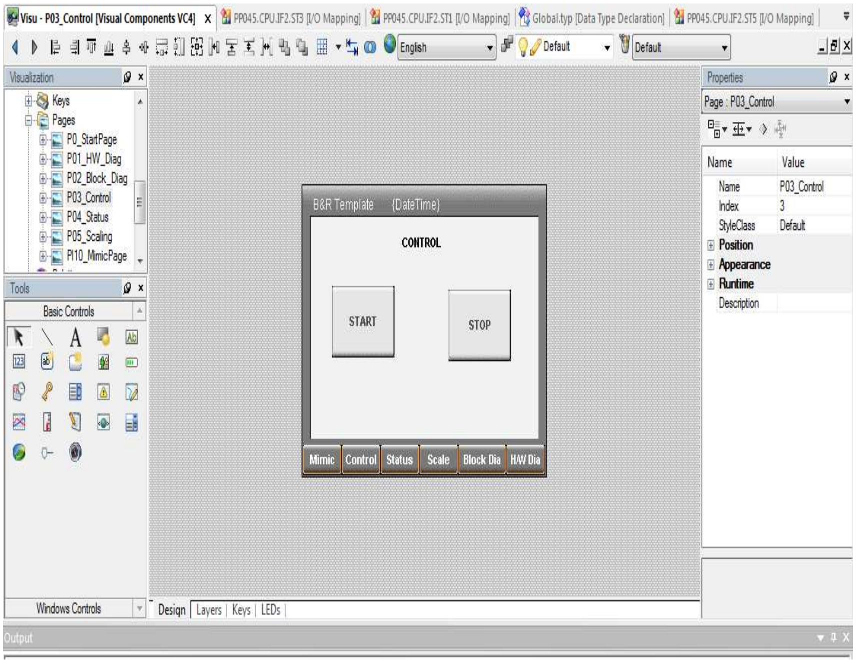

Fig. 15. Start/Stop button in PLC-HMI

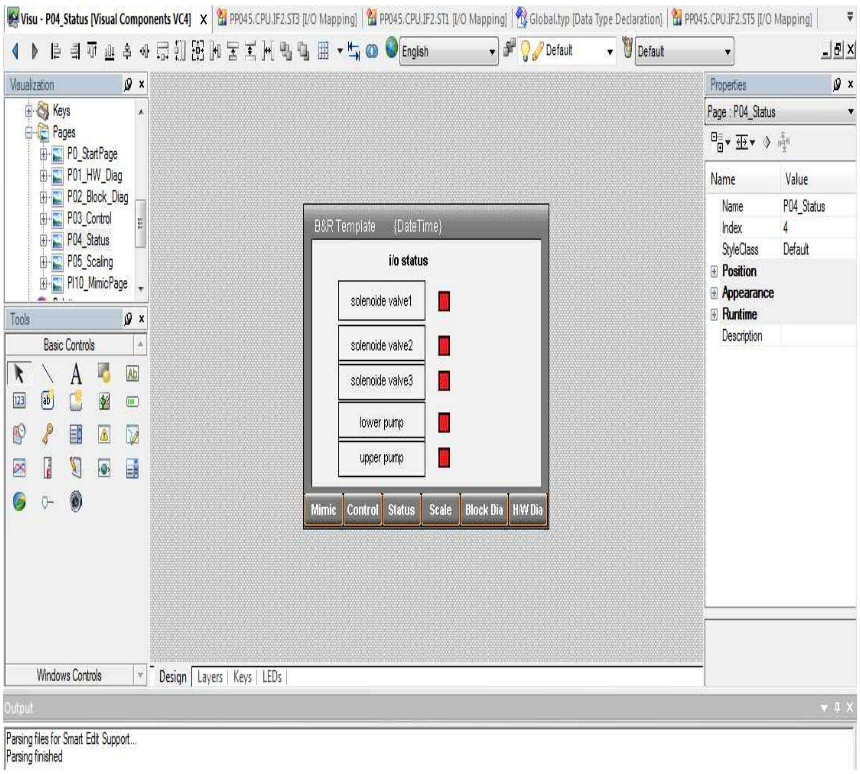

Fig. 16. Valves and pumps in PLC-HMI

6. PROTOTYPE OUTPUTS

Numerous numbers of experiments were carried out on the prototype model and the performance for both variations in the set point as well as in load were analysed. The responses obtained for up and down variation in load for conventional and neural cascaded with fuzzy scheme in hydro power plant are shown in **Fig. 17-19**.

Appraisal of time domain specifications like Rise time, peak time and settling time for conventional and the proposed PLC-HMI based neural cascaded with fuzzy scheme was analyzed. Likewise the performance evaluation criteria like Integral Square Error (ISE) and Integral Absolute Error (IAE) was done for both conventional and the proposed PLC-HMI based neural cascaded with fuzzy scheme for different step changes in load and it is presented in **Table 1 and 2**.

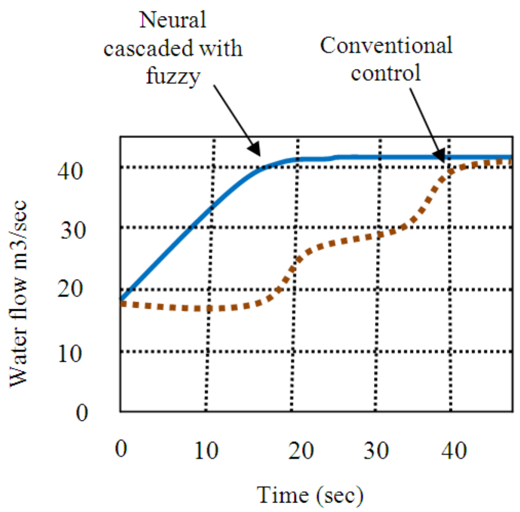

Fig. 17. Load 10-20 MW Gate 1 Opening above average level Set Point 20-40 m3/sec

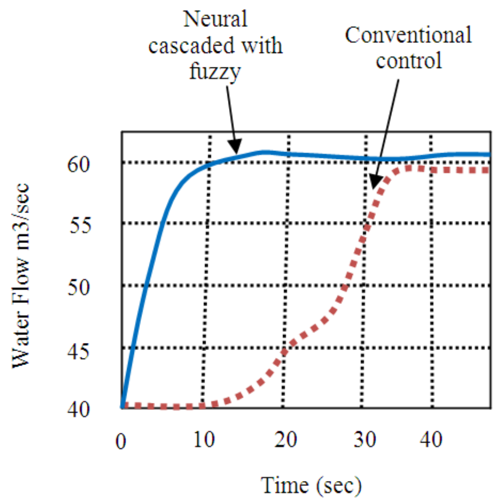

Fig. 18. Load 20-40 MW Gate 2 opening at medium level set point 40-60 m3/sec

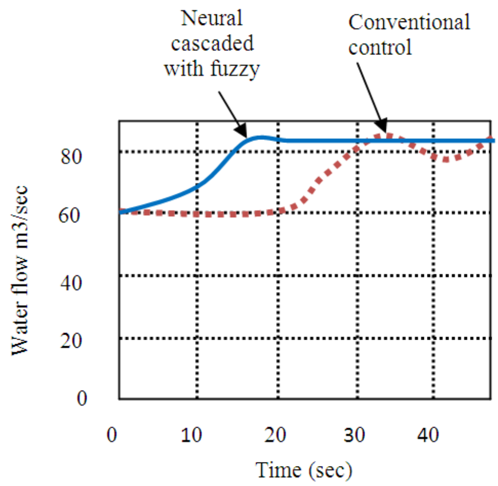

Fig. 19. Load 40-60 MW Gate 3 opening at high level set point 60-85 m3/sec

Table 1. Comparisons of performance evaluation criteria

		Load 10-20 MW		Load 40-60 MW	
Control scheme	Control loop	ISE	IAE	ISE	IAE
Conventional PLC	Water flow	9600	8780	9442	8325
Neural cascaded with fuzzy	Water flow	7306	7200	7333	7006

Table 2. Comparisons of time domain specifications

		Load 10-20 MW			Load 40-60 MW		
Control scheme	Control loop	Rise time	Peak time	Setl time	Rise time	Peek time	Setl time
Conventional PLC	Water flow	32	40	43	26	33	42
Neural cascaded with fuzzy	Water flow	14	18	22	13	18	20

Analyzing the results obtained, Rise time is faster in proposed scheme but in conventional scheme because of dead time, it gave sudden open in gate that leads to water inertia and the flow didn't do immediate change. In this new neural cascaded with fuzzy scheme, gate position is acknowledged and a proper signal is manipulated to operate the gate which fulfilled the sudden load change and uphold constant speed with a reduction of settling time. Similarly analyzing the Performance Evaluation criteria, the conventional method has large ISE and IAE errors when compared with the proposed scheme. This emphasizes the better performance of PLC-HMI based Neural cascaded with fuzzy scheme than the conventional method.

7. CONCLUSION

The results obtained spotlights the better performance and importance of the PLC-HMI based Neural cascaded with fuzzy scheme than the conventional scheme on different load variation. Analyzing the conventional method response, it has 27% overshoot for water flow. It settles down after about 69 steps of increment for water flow. The PLC-HMI based Neural cascaded with fuzzy water flow controller scheme proves better transient response without much peak overshoot and attains steady state after about 44 steps of increment for water flow.

Similarly analyzing the proposed PLC-HMI based Neural cascaded with fuzzy controller scheme, it has 39% improvement over conventional scheme in settling time for water flow by comprising minimum ISE and IAE values for the step changes in load showing 18% improvement for water flow when compared to conventional scheme. The overall qualitative and quantitative evaluation exposes the supremacy and importance of the PLC-HMI based Neural cascaded with fuzzy scheme over the conventional scheme.

8. REFERENCES

Goyal, H., 2006. A three gate neural network based approach for automatic control of small hydro power plants. Int. J. Emerg. Electric Power Syst. DOI: 10.2202/1553-779X.1148

Guo, L., 2009. Design projects in a programmable logic controller course in electrical engineering. Technol. Interface J.

Isasi-Viñuela, P., J.M. Molina-López and A.S. De Miguel, 1997. Unsupervised neural network for forecasting alarms in hydroelectric power plant. Proceedings of the International Work-Conference on Artificial and Natural Neural Networks: Biological and Artificial Computation: From Neuroscience to Technology, Jun. 4-6, Springer Berlin Heidelberg, Canary Islands, Spain, pp: 1298-1306. DOI: 10.1007/BFb0032590

Jasa, L., A. Priyadi and M.H. Purnomo, 2012. PID control for micro-hydro power plant based on neural network. Proceedings of the IASTED Asian Conference Modeling, Identification and Control, Apr. 2-4, Phuket, Thailand, pp: 1-7. DOI: 10.2316/P.2012.769-039

Karthigayani, P. and S. Sridhar, 2014. Decision tree based occlusion detection in face recognition and estimation of human age using back propagation neural network. J. Comput. Sci., 10: 115-127. DOI: 10.3844/jcssp.2014.115.127

King, D.J., D.A. Bradley, S.P. Mansoor, D.I. Jones and F.C. Aris *et al*., 2001. Using a fuzzy inference system to control a pumped storage hydro plant. Proceedings of the 10th IEEE International Conference on Fuzzy Systems, Dec. 2-5, IEEE Xplore Press, pp: 1008-1011. DOI: 10.1109/FUZZ.2001.1009132

Liang, R.H., 2000. A noise annealing neural network for hydroelectric generation scheduling with pumped-storage units. IEEE Trans. Power Syst., 15: 1008-1013. DOI: 10.1109/59.871726

Molina, J.M., P. Isasi, A. Berlanga and A. Sanchis, 2000. Hydroelectric power plant management relying on neural networks and expert system integration. Eng. Applic. Artifi. Intelli., 13: 357-369. DOI: 10.1016/S0952-1976(00)00009-9

Priyadharson, A.S.M., M.S. Saravanan, N. Gomathi and S.V. Joshua *et al*., 2014. Energy efficient flow and level control in a hydro power plant using fuzzy logic. J. Comput. Sci., 10: 1703-1711. DOI: 10.3844/jcssp.2014.1703.1711

Rajeswari, V., Y. Rajeshwari and L.P. Suresh, 2012. Real-time implementation of hydroelectric power plant using PLC and SCADA. Int. J. Eng. Res. Applic., 2: 899-902.

Singh, G. and D.S. Chauhan, 2011. Simulation and modeling of hydro power plant to study time response during different gate states. Int. J. Adv. Eng. Sci. Technol., 10: 042-047.

Stokelj, T., S.E. Seng, N.G. Slovenia and R. Golob, 2000. Application of neural networks for hydro power plant water inflow forecasting. Proceedings of the 5th Seminar on Neural Network Applications in Electrical Engineering, Sept. 25-27, IEEE Xplore Press, Belgrade, pp: 189-193. DOI: 10.1109/NEUREL.2000.902410