Design and Development of Neuro-Fuzzy controller for Hydropower Generator Stability

Enebechi Chukwuemeka Theophilus and Prof Eneh, I. I.
Department of Electrical Electronic Engineering
Enugu State University of Science and Technology, (ESUT), Enugu State, Nigeria.
theomeka@yahoo.co.uk

ABSTRACT: Following the need to design and develop a controller that will continuously assist an operator to supervise and modulate the systems stability in hydropower dams. A hybrid of variable Fuzzy logic based controller and a classified Neural network called Neuro-Fuzzy technique is presented. In the design a rule and membership function based fuzzy logic for reservoir control is demonstrated. The designed model simulates the control variables using different rules and method. In order to regulate the rule base and membership functions which have great influence on the performance of hydropower generation systems. This research involves encoding of fuzzy rules and procedures, followed by fuzzy inference processes in the fuzzy logic Tool box, then, the Neural network is imbibed into the Fuzzy Toolbox and SMULINK in MATLAB software. The controller is designed to display the regulated simulation result of water level and flow rate. This has resulted to improving the stability of hydropower turbine speed to ensure the optimum performance of hydropower generation within expected range and real time.

Keyword: Hydropower system, water level, Flowrate, Neuro-Fuzzy, Fuzzy Toolbox, MATLAB software, Fuzzy Inference System.

Introduction

Due to critical conditions, emotional and psychological stress, an engineer or operator in various scientific or industrial areas, where most of the real time systems are generally complex and difficult to be controlled, of which hydropower plant is one, operator may not be able to instantly, and continuously respond to making correct decisions as disturbances arise. Mistakes can damage very expensive power equipment or worst still, lead to major emergencies and catastrophic situations.

As a result, there is a strong need for automated control device that can assist operators to improve on the robust control of hydropower turbine speed in order to stabilize and ensure optimal performances within the predetermined ranges using various intelligent techniques.

In view of this, an intelligent robust power monitoring device that will continuously supervise and modulate their respective control actions is proposed in this study. Thus, an Adaptive control based scheme, in which a variable fuzzy based controller is cascaded with a Neural network identifier called ***Neuro-fuzzy technique*** is demonstrated in order to improve the stability of hydro power generation. Adaptive neuro-fuzzy techniques are also referred to as "Adaptive Network based-fuzzy inference system" (ANFIS) [1]. turbine speed within expected range. This cannot work without an in-depth study and knowledge of Hydropower liquid level controller and controllers for flowing fluids, dam, Turbines, generator and the

Hydropower generation uses moving water to produce power. There are many ways to harness the power of moving water, but regardless of which method is being used; most hydropower is generated by using these general processes:

- Water is directed into a water turbine.
- The force of the water makes the turbine spin.
- The turbine is connected to a generator.
- The generator produces electricity.

ISSN 2229-5518

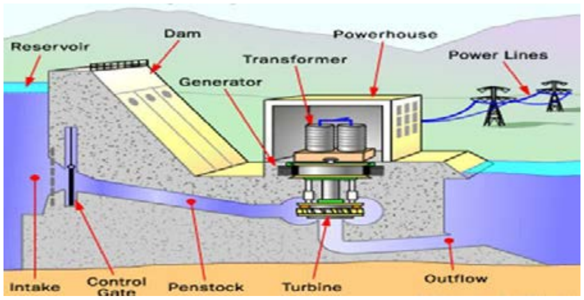


Fig. 1: General overview of Hydropower plant

Two important inputs parameters namely the water level and flow rate ultimately play important roles in turbine and shaft rotation, also stator, rotor and excitation are taken into consideration in this research. The output sensors are mechanically linked to the Drain valve control and water release control valve for efficient and robust hydropower stability. To maintain these parameters within the prescribed optimum level using water level and flow rate input variables, a measuring device for feedback control (Fuzzy inference Editor) for the two output, the drain and control release valves of the controller, is required. The Fuzzy Inference Editor or the rule Editor allows us to interpret the entire fuzzy inference process at once and also shows how the shape of certain membership functions influences the overall result. Nevertheless, the rule in rule editor provides the control strategy. FLC uses the rules for a straight forward implementation proposed to solve a class level of control problems with unknown dynamics or variable time delays commonly found in industries, given attention to various parameters, such as the time of response, the error of steadying and overshooting.

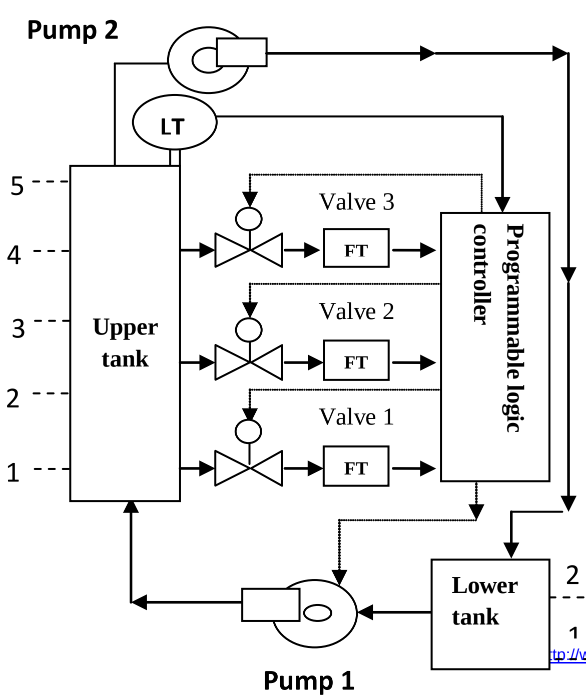
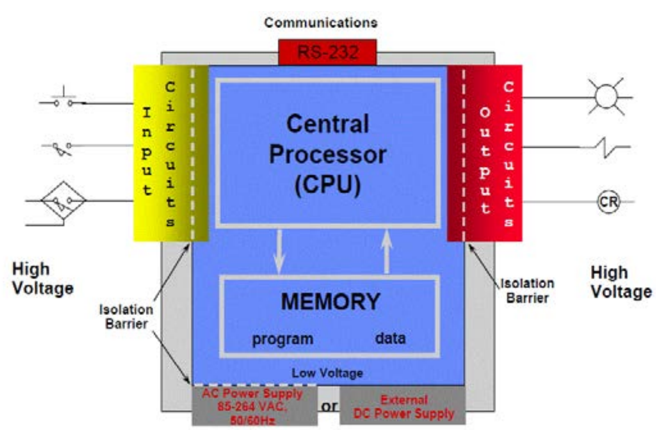


Fig 2: Operation of a typical model of a small scheme hydro generating plant.

The lab scale experimental set up operation is shown in Fig. 2 [2]. It is provided with lower tank of two levels and upper tank of five levels. There are two tanks in the lab scale experimental set up. There are 5 stages in tank 1 and two stages in tank 2, [2]. The five stages in upper tank are: Low level, Average level, Medium level, High level, Danger level. The two stages in lower tank are; Low level, High level. There are some sequences followed in hydroelectric power plant which are implemented in Lab scale experimental set up, [2]. When the water level in the Upper tank reaches the low level, the upper pump is actuated and the water is taken to the lower tank from the upper tank. In lower tank when the water level reaches the low level, upper pump is again switched on and water level raises up to average level. When water exceeds average level, valve 1 is allowed to open. Similarly when the level attains medium level, the upper pump is actuated and the water rises up to high level. When water is mounting beyond medium level, Valves I and 2 are opened and when water level increases beyond high level, Valves 1, 2 and 3 are opened. When the level increases beyond the high (danger level), the upper pump is actuated and water is taken back to lower tank. If the water level reaches high level in lower tank, Valve 1, 2 and 3 will be closed and the upper and lower pumps will be switched off. Based on the level Transmitter (Lower Tank) output, the ladder logic is programmed and just as programmed in the ladder logic, the pumps and the opening of valves of the dam are actuated at their respective levels.

Figure 3: CPU imbedded with PLC



ISSN 2229-5518

The conventional scheme, fuzzy cascaded with PLC-HMI (Programmable logic controller- Human machine interface) was proposed

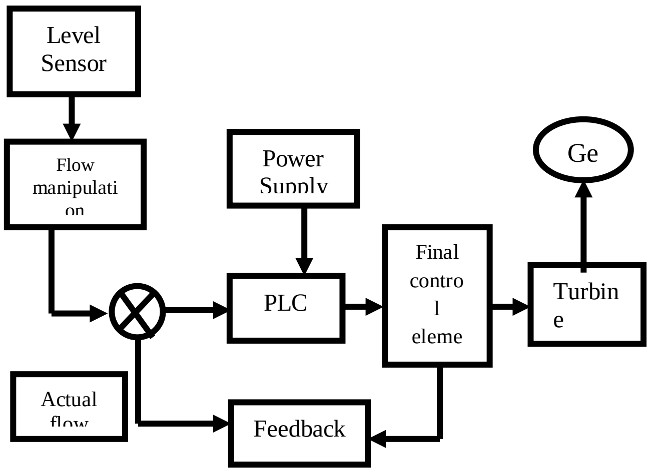


Fig 4: block diagram for flow control in Hydro Plant

to perform and maintain the water level in the tank and flow rate of the water to the turbine based on Load demand. In that scheme, the PLC system is utilized for automation in small hydropower plant with respect to the operational requirements. The components are; Processor Unit (CPU), Memory section, Input/output sections, Power supply unit, Programming device and System buses, [3]. A PLC is an example of a "hard" real-time system since output results must be produced in response to input conditions within a limited time, otherwise unintended operation will result. In figure 4 above, the block diagram for flow control in hydro power is represented. The Gate (final control element) opens/closes in hydroelectric plant depending on the water level in the Dam. The water level in the dam is measured by capacitive level sensor. The actual level value is manipulated to the flow set point by using flow manipulator. Comparison between water set point and actual flow is done and the error is controlled by PLC which gives manipulated variable to the Gate valve. The water out flow from the gate valve is taken to the turbine.

Neuro-Fuzzy

The Neuro-fuzzy integrated system can be trained by numerical data and linguistic information expressed by fuzzy IF-THEN rules. Neuro-fuzzy system (NFS) incorporates the human-like reasoning style of fuzzy systems through the use fuzzy set and a linguistic model consisting of a set of IF-THEN fuzzy rules. The strong point of Neuro-fuzzy system is that they are universal appropriators with the ability to solicit interpretation of IF-THEN rules, [4]. There are Fuzzy Neural rules with FN neurons in the inference and defuzzification layers and one neuron in the output layer. For simplicity, it is assumed that the fuzzy inference system under consideration has two inputs x and y and one output z as shown in Fig. 5. For a zero-order Sugeno fuzzy model, a common rule set with two fuzzy IF-THEN rules is the following:

Rule 1: If x is A1 and y is B1, THEN f1 = r1 (1)
Rule 2: If x is A2 and y is B2, THEN f2 = r2 (2)

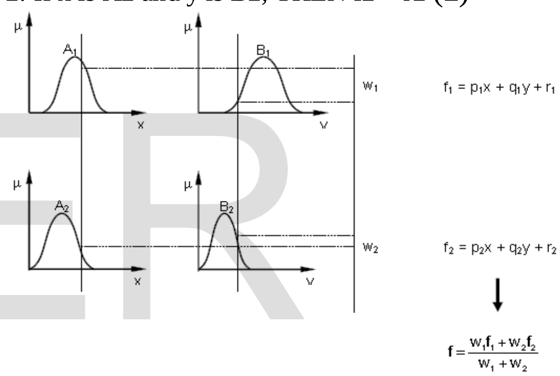


Fig. 5: Sugeno's Fuzzy Logic Model

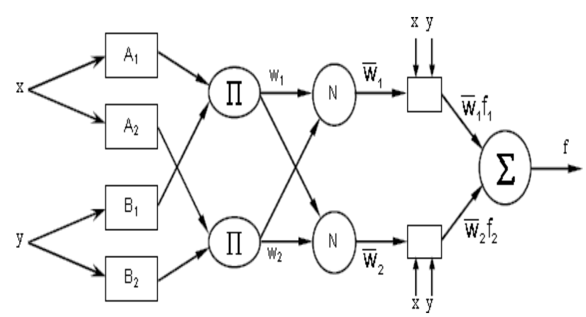


Fig. 6: The Architecture of the ANFIS

Here, the output of the i^{th} node in layer n is denoted as $O_{n1}{}^2$

Layer 1**:** Every node *i* in this layer is a square node with anode function.

O_I^1 = $\mu A_i(x)$, for *i* = 1, 2 (3)

Or

O_I^1 = μB_{i-2} (y), for i = 3, 4 (4)

ISSN 2229-5518

Where *x* is the input to node-*i*, and *Ai* is the linguistic label (*small*, *large*, etc.) associated with this node function. In other words, O_I^1 is the membership function of A*i* and it specifies the degree to which the given x satisfies the quantifier A_i. Usually μA*i*(x) is chosen to be bell-shaped with maximum equal to 1 and minimum equal to 0, such as the generalized bell function: *Agus* et al; 2012.

$$\mu_A(x) = \frac{1}{1+\left[\frac{x-c_i}{a_i}\right]^{2b_i}} \qquad (5)$$

Parameters in this layer are referred to as premiseparameters.

Layer 2: Every node in this layer is a circle node labeled II which multiplies the incoming signals and sends the product out. For instance,

$$O_I^2 = w_i = \mu A_i(x) \times \mu B(y), \text{ for } i = 1, 2 \qquad (6)$$

Each node output represents the firing strength of a rule. (In fact, other *T-norm* operators that performs generalized AND gate which can be used as the node function in this layer.)

Layer 3: Every node in this layer is a circle node labeled N. The ***i***- th node calculates the ratio of the i-th rule's firing strength to the sum of all rules firing strengths:

$$O_I^3 = \overline{w} = \frac{w_i}{w_1 + w_2}, \ i = 1, 2 \qquad (7)$$

For convenience, outputs of this layer will be called normalized firing strengths.

Layer 4: Every node *i* in this layer is a square node with anode function:

$$O_I^4 = \overline{w}_1 f_1 = \overline{w}_1(p_1\,x + q_1\,y + r_1) \qquad (8)$$

Where $\overline{w}_1$ is the output of layer 3, and $(p_1 q_1 r_1)$ is the parameter set. Parameters in this layer will be referred to as consequent parameters, [5].

Layer 5: The single node in this layer is a circle node labeled Σ that computes the overall output as the summation of all incoming signals, i.e.

$$O_I^5 = \sum \overline{w}_1 f_1 \qquad (9)$$

In flow process fuzzy logic is taking as the controlling unit. The fuzzy controller implements the control algorithm, compares the output with the set point and then gives necessary command to the final control element via actuator unit (Sa). Neural network is equipped with the capability of handling fuzzy information [termed fuzzy neural network (FNN) and a fuzzy system augmented by neural networks to enhance some of its characteristics like flexibility, speed, and adaptability [termed neural-fuzzy system [NFS]. An important feature of Neuro-fuzzy integrated system is that, without any given initial structure, the system can construct itself automatically from numerical training. However, this study did not only demonstrate an appreciable improvement in hydropower system stability, efficiency and reliability but also optimizes the sudden load change and also maintain the expected constant speed.

Designing a Fuzzy Logic Controller

Design of a fuzzy logic controller requires a sufficient knowledge about the response of the control process. The data from the process study constitute the knowledge base for the fuzzy logic controller, [6].

The steps involved in designing a simple fuzzy logic controller are as follows:

- Identify the variables (input states and outputs) of the plant
- Partitioning each variable into a number of fuzzy subsets, assigning each a linguistic label (subsets include all the elements in the universe).
- Assign or determine a membership between the inputs states of fuzzy subsets in one hand and the outputs fuzzy subsets on the other hand, thus forming the rule base.
- Choose appropriate scaling factors for the input and the output variables in order to normalize the variables to the [0, 1] or the [-1, +1] interval.
- Fuzzy the inputs to the controller
- Use fuzzy appropriate reasoning to infer the output contributed from each rule.
- Aggregate the fizzy outputs recommended by each rule.
- Apply defuzzification to form a crisp output.

In the defuzzification step, the Water level and Flow rate are selected as input variables. Generally, these input variables are divided into three fuzzy sets and they are linguistically named as HIGH, LOW and OK as shown in figure 7 and Figure 8. The Gaussian membership functions with the appropriate ranges are used for fuzzy sets. The values of the valve have been selected as Fuzzy output variables.

ISSN 2229-5518

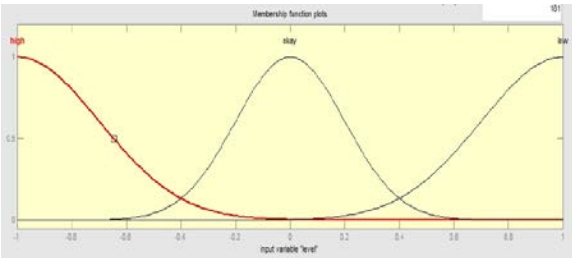


Figure 7: Fuzzy set input variables membership function of error.

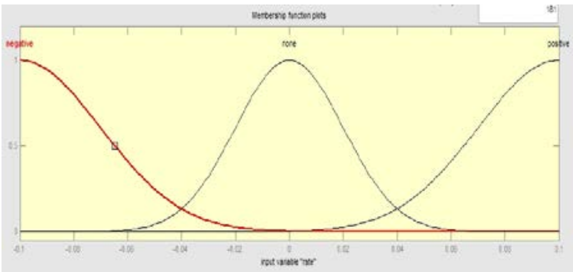


Figure 8: Fuzzy set output membership function of change in error.

Just like the input variables the output variables are divided into five fuzzy sets with linguistic names; OPENfast, OPENslow, NOchange, CLOSEslow and CLOSEfast as shown below

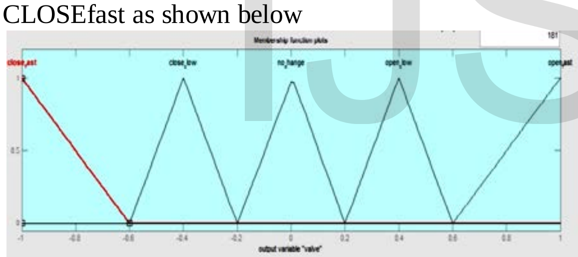


Figure 9: Output membership function of valve.

The six rules are:

1. If (Flow level HIGH) then (Valve is CLOSEFAST)

2. If (Flow level is OK) then (Valve is NOCHANGE)

3. If (Flow level is LOW) then (Valve is OPENFAST)

4. If (Flow level is OK) and (Flow rate is POSITIVE) then (Valve is CLOSESLOW)

5. If (Flow level is OK) and (Flow rate is OK) then (Valve is NO CHANGE)

6. If (Flow level is OK) and (Flow rate is NEGATIVE) then (Valve is OPENSLOW)

The centroid method has been used to obtain the crisp value. [7]

Related works

[8]. In this study, we demonstrated and proposed the design and development of Fuzzy Logic controller for the flow control of Dams. The research used fuzzy methods Mamdani Inference Methods (MIM) to evaluate his results using manual C.O.G defuzzification and MATLAB FIS Editor Validation. In this design, two input parameters: water level and flow rate and two output parameters: Release control valve and Drain valve were used. The aim of this control system is to keep the hydropower Dam within the pre-determined ranges by controlling the flow through a control valve at the dam and the inflow through drain valve in any condition.

[9], carried a study on ‘‘Co-active Neuro Fuzzy inference system for governing & excitation controls of power system stability’’. In the research work, coordination of governing control and excitation control using neuro-fuzzy theories compensates their control inputs during faults. The angular speed (ω), accelerating speed (Pm – Pc) and the terminal voltage (V_1) of generator are observed to characterize the severeness of oscillation. It was observed that compensation is robust in different system faults. In slide system fault cases the compensation helps the original controls to damp the system oscillation, when the disturbances is trivial, which won't cause large oscillation. When only the output for governing control is added, the first swing is better, but those after first swing are worse than the oscillation in the case without compensation which seems to be a limitation observed in the system.

[10], "An Effective Fuzzy- GA Flow Control of Turbine Compressor system: A Process control case Study". In their study, it was proved that Fuzzy logic provides a formal method of translating subjective and imprecise human knowledge into control strategies, thus facilitating better system performance through the exploitation and application of that knowledge.

[11], studied the steam flow parameters of a boiler which were controlled by using both conventional PID controller and the optimized using fuzzy logic controller. The comparative results (overshoot, settling time) show the better results when Fuzzy logic controller is used than PID.

[12]. Design of Neuro – Fuzzy inference distributed power flow controller for transient stability improvement. In this study, Neuro-Fuzzy systems are the systems that neural networks (NN) are incorporated in Fuzzy systems, which can use knowledge automatically by learning algorithms of Neural Networks. Neuro-Fuzzy inference system (NFIS) is one of the examples of Neuro fuzzy systems implemented in the frame work of adaptive networks. NFIS is used in specialized learning algorithm as a controller.

[13]. Design of Neuro – Fuzzy inference distributed power flow controller for transient stability improvement. In this study, Neuro-Fuzzy systems are the systems that neural networks (NN) are incorporated in Fuzzy systems, which can use knowledge automatically by learning algorithms of NNs. Neuro-Fuzzy systems inference system which (NFIS) is one of the examples of Neuro fuzzy systems in a fuzzy system is implemented in the frame work of adaptive networks. NFIS is used in specialized learning algorithm as a controller.

3.1 DESIGN PROCEDURE AND METHOD

This method focuses on what the system is expected to do rather than trying to understand how it works. It requires more concentration on solving the problem rather than trying to model the system mathematically, if it is possible.

Firstly, the general description and analysis of the operation of the prototype model is demonstrated in Fig 2. An analysis of the conventional design showcasing the real-time work of the PLC-HMI based fuzzy controller scheme for flow and level control is shown in Figure 10.

This scheme as shown below is the design for the Hydropower plant system stability. The first step taken was to design the Fuzzy Inference System (Rule Editor). The FIS has two Inputs. One is Level of the liquid in the DAM defined as "level" and the other one is change of flow of liquid in the dam denoted as "rate". Both Inputs are applied to the Rule Editor. According to the Rules written in the Rule Editor the controller takes the action that governs the opening of the valve gate which is the Output of the controller and are denoted by "control valve and drain valve". This is shown in figure 10.

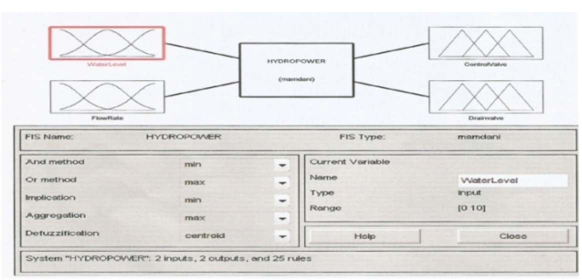


Fig. 10: Hydro Power Plant Rule Editor

In Fuzzification processes, a numerical variable (real number or crisp variable) is transformed into a linguistic variable (fuzzy number). The occupied region description, Triangular membership functions and range for two input variables are given in tables 1, 2, 3, 4 and 5.

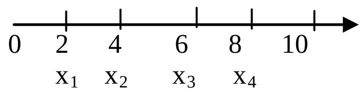
However, the inference engine involves four and operators that select minimum input values for the output. Four inputs (F) of fuzzifier were accepted by inference engines and applied to the min- max composition to obtain the output value (F).

Inference Engine for four inputs (F) of Fuzzifiers are calculated. In arriving at our values, appropriate domains are chosen on the x axis, since it gives us the best level of stability as desired in this work.

The ranges are $0 < x < 10$, A domain of x is chosen from the number line as shown below:

$x > 0$

$x < 10$



From the inequality $F_1 = 10$

To find F_2, two members are chosen from the domain to give us a steady state flow in the system. Thus, we have $x_1 + x_4$ and $x_2 + x_3$.

Therefore, $F_2 = x_1 + x_4 = 2 + 8 = 10$.

Similarly, $F_3 = x_2 + x_3 = 4 + 6 = 10$.

Using alternate formula,

$F_2 = F_4 = 10$.

Thus, the four fuzzification results

F_1, F_2, F_3, and F_4 have the same value of 10.

Input Variables	Region selection	Fuzzy set Calculation
Water level	$0 < x < 10$	$F_1 = 10$ $F_2 = x_1 + x_4 = 2 + 8 = 10$. $F_3 = x_2 + x_3 = 4 + 6 = 10$. $F_2 = F_4 = 10$.
Flow rate	$0 < x < 10$	$F_1 = 10$ $F_2 = x_1 + x_4 = 2 + 8 = 10$. $F_3 = x_2 + x_3 = 4 + 6 = 10$. $F_2 = F_4 = 10$.

Table 1: Fuzzification results

The Rule editor also shows how the shape of certain membership functions influences the overall result. Rules shown in Rule editor provide inference mechanism strategy and generate the control signal output. In this research total number of active rules obtained is equal to 25 rules ($=5^2$) as shown in the figure below on table 2 and 3 on page 10.

Table 2: Total Number of Rule for Release control Valve

Flow	***Very***	***Slow***	***Normal***	***Fast***	***Very***

rate/water Level	***Slow***				***Fast***
Above Danger	Close Fast	Close Fast	Close Fast	Close Fast	Open Slow
Danger	Close Fast	Close Fast	Close Fast	No Change	No Change
Below Danger	Open Slow	**No Change**	**Close Slow**	Close Slow	Open Slow
Low	Open Fast	Open Fast	Open Fast	Open Fast	Open Fast
Very Low	Open Fast	Open Fast	Open Fast	Open Fast	Open Fast
X	X_1	X_2	X_3	X_4	X_5

The table above shows the 25 variable numbers of Rules generated for Release control valve see, figures 12, 13, and 14 and their triangular membership functions in figure 14,15 and 16

Table 3: Total Number of Rule for Drain Valve

Flow rate/water Level	Very Slow	Slow	Normal	Fast	Very Fast
Above Danger	Close Fast	Close Fast	Close Fast	Close Fast	Open Slow
Danger	Close Fast	Close Fast	Close Fast	No Change	No Change
Below Danger	Open Slow	**No Change**	**Close Slow**	Close Slow	Open Slow
Low	Open Fast	Open Fast	Open Fast	Open Fast	Open Fast
Very Low	Open Fast	Open Fast	Open Fast	Open Fast	Open Fast
X	X_1	X_2	X_3	X_4	X_5

Table 3 shows the 25 variable numbers of Rules generated for Drain valve see, figures 10,11, and 12, and the membership function in Figure 18

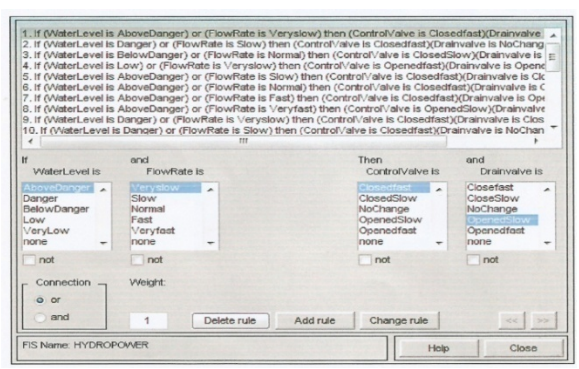


Fig.11: Membership Functions generated for 1 - 10 by fuzzy Rule Editor.

The total number of rules is equal to the product of number of functions accompanied by the input variables in their working range. The two input variables described here consist of five membership functions, while the generated membership functions for the Water level, Flow rate, Control Valve, and Drain Valve, are displayed below in Figure 11, 12 and13 respectively.

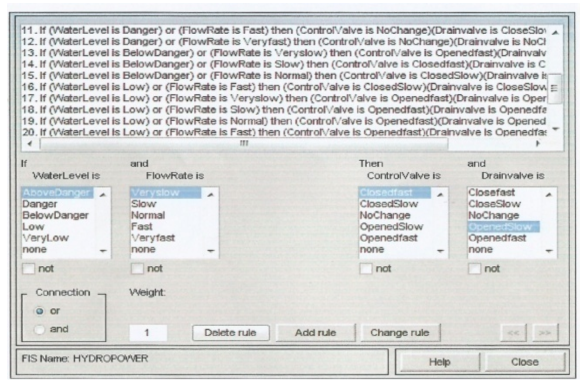


Figure 12: Membership Functions generated for 11 - 20 by fuzzy Rule Editor

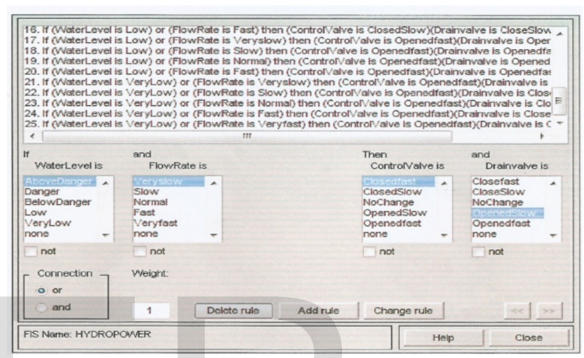


Fig.13: Membership Functions Generated for 20-25 by fuzzy Rule Editor

The triangular membership functions are used to represent the linguistic terms (VS Very small; S small; M medium; I. large; VI. Very large). Rule base is developed and an inference mechanism is designed using Mamdani (min-max) method that gives the output signal to the final control elements.

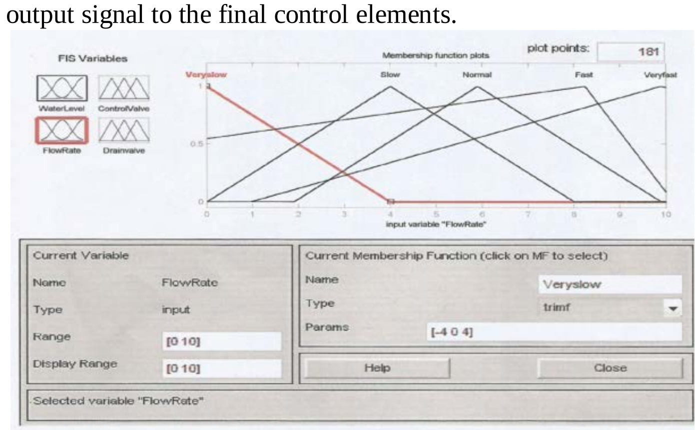


Fig. 14: Generated Water level membership functions

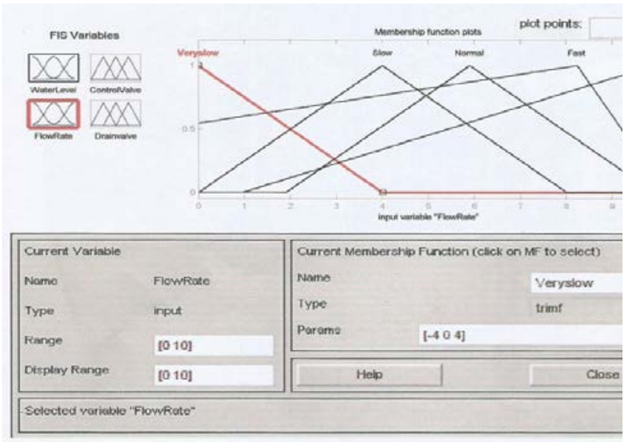


Figure 15: Generated Flow rate membership functions

Analysis of the Drain Valve in Fuzzy Inference System

The algorithm designed for this system consists of two fuzzy input variables:"water Level" and "flow Rate" and one output variable "Drain Valve". The main aim of this control system is to regulate the flow of water being fed to the turbine in accordance with the load perturbations and thereby maintaining the constant output frequency of the system at the desired level through FLC. A scale range of 0 m to 10 m is used for the x- axis and 0 (m^3s-1) to 1(m^3s-1) for the y- axis for water level and flow rate inputs respectively. The control valves output variables consist of five membership functions: closed fast, closed slow, no change, opened slow, opened fast.

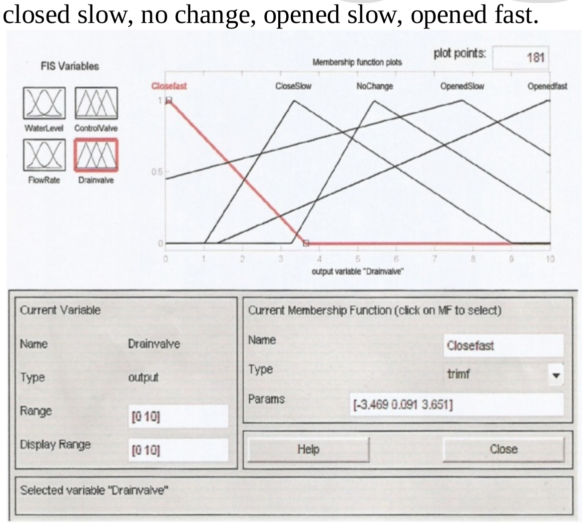


Fig. 16: Generated Drain valve membership functions

Analysis of the Control Valve in fuzzy Inference system: The application of FLC system for dam consists of two input variables: "Dam Lake Level" and "Water Inflow Rate". "Openness of the Control Valve" is an output variable and controlled by the FLC rule base. The main aim of this control problem is to discharge excess water (danger level or above) within the shortest possible time for the overall safety of the system and thus bringing it back to safe or desired level (below danger level) through FLC. Five triangular membership functions are determined over a scale range of 0 m to 10 m for the x- axis and 0 (m^3s-1) to 1(m^3s-1) for the y- axis for water level and flow rate inputs respectively. The control valves output variables consist of five membership functions: closed fast, closed slow, no change, opened slow, opened fast.

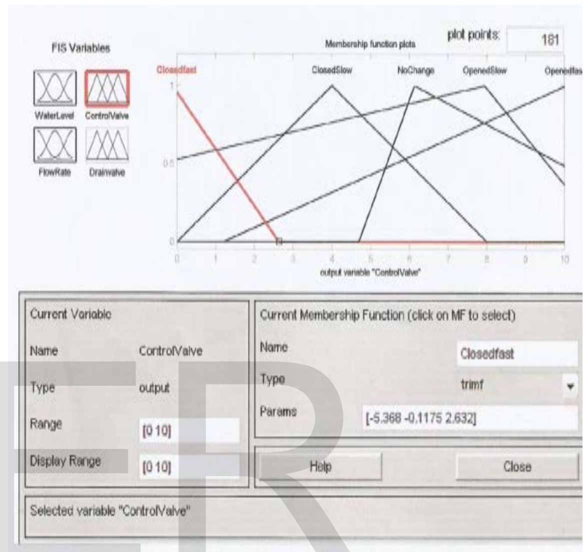


Figure 17: Generated Release Control valve membership functions

The rules are based on 'Mamdani inference method'. The simulation results are obtained using a 25 rule Fuzzy Logic control. Rules shown in Rule editor provide the control strategy.

The parameters of the FLC system designed for the hydro electric power plant are presented as shown above.

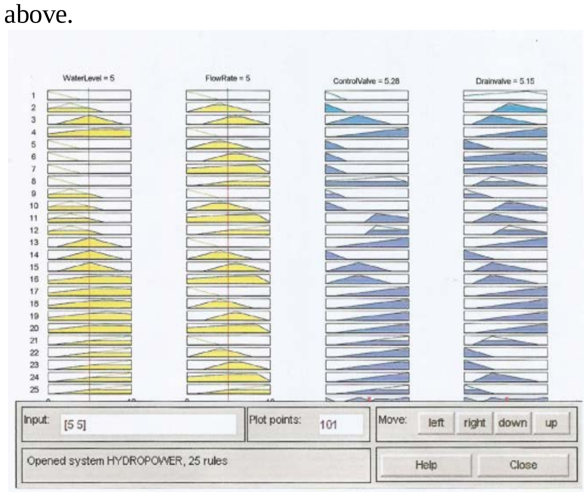


Fig. 18: The triangular membership functions for 25 Rules.

Using a range of 0m to 10m and 0(m^3s-1) to 1(m^3s-1) for both the for Water level and Flow rate, the 5 membership functions format is delegated to each of the functions, as follows: Output Format; Close Fast = 0, Close Slow = 2, No change = 4 , Open Slow = 6, Open Fast = 8; figure 16, shows the membership functions for Drain Valve.

The act of simulating something first requires that a model be developed; this model represents the key characteristics of the selected process. A module for the PLC-HMI scheme Fuzzy logic base is designed as shown in figure 19. Recall that the fuzzy rule is imbibed inside the fuzzy logic controller to enhance the efficiency of controlling the expected stability.

Fuzzy rule helps to guard the liquid level of the Dam. Without imbibing the rule inside the fuzzy logic controller, the hydropower generator will NEVER run, let alone give an accurate result. The input variables of water and flow rate are fed into the fuzzy logic controller which is inserted inside the hydropower generator model. This is then simulated to obtain the output result for the Release control and Drain valves which represent the operation of the system overtime.

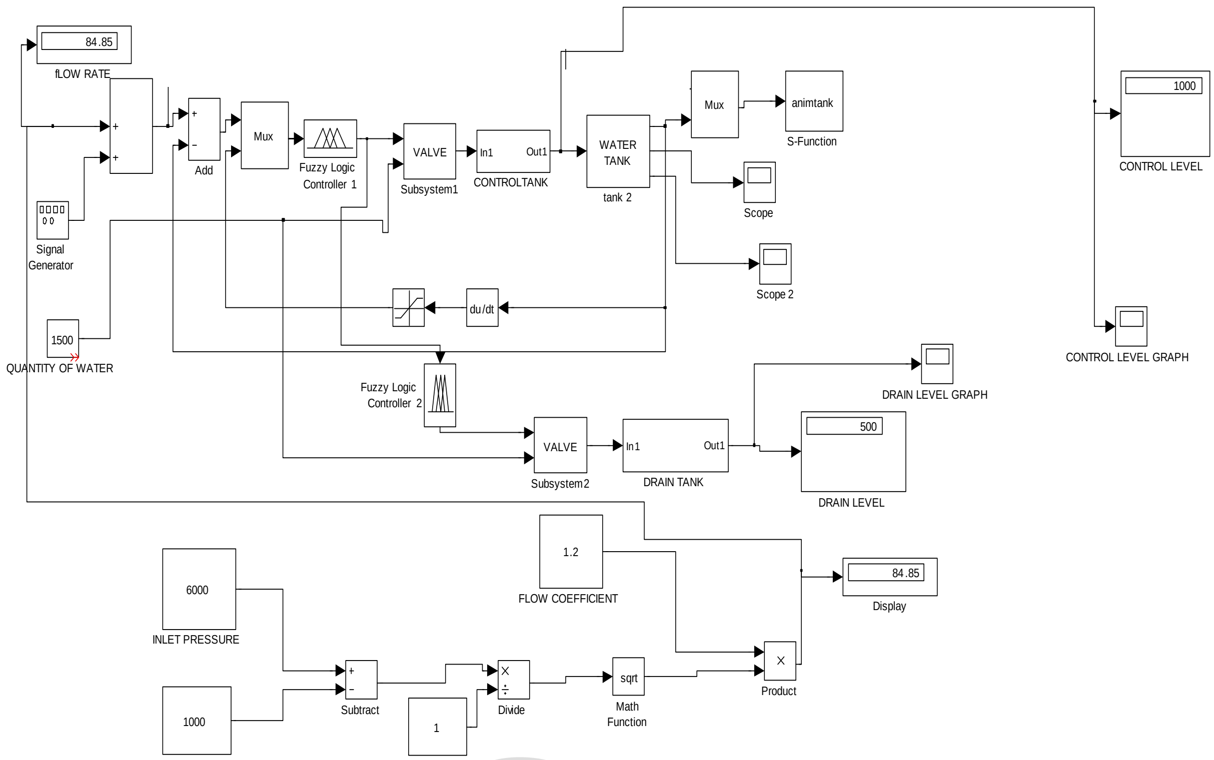


Figure 19: conventional Fuzzy cascaded with PLC-HMI controller

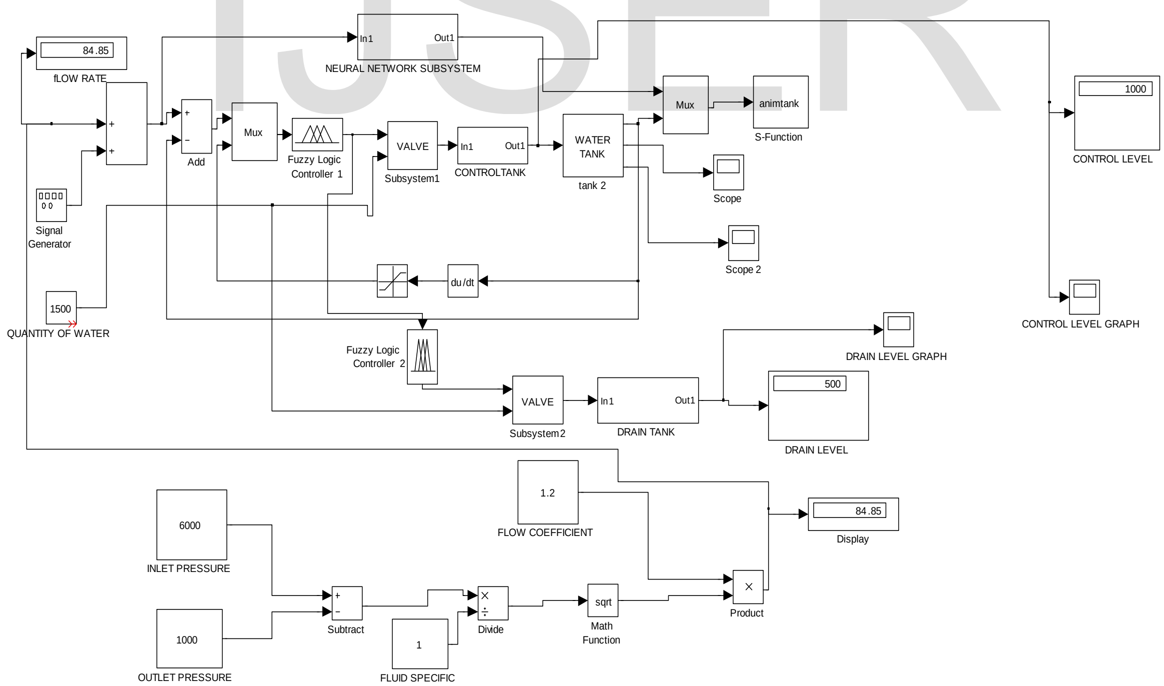


Figure 20: Designed and Developed Neuro- Fuzzy model for Hydropower Stability Controller

ISSN 2229-5518

INVESTIGATING THE STABILITY OF HYDROPOWER GENERATOR USING NEURO- FUZZY TECHNIQUE

As a result of limitations observed at the outputs of the conventional Fuzzy logic scheme, there is need to improve on the stability of hydropower generator by cascading the conventional Fuzzy logic scheme with a classified Neural network, known as "**Neuro-Fuzzy**" model shown in figure 20.

However, the neural network was inserted into the conventional scheme of the fuzzy base and simulated as shown in figure 20 to generate the designed Neuro-fuzzy hydropower stability rules shown in figure 21.

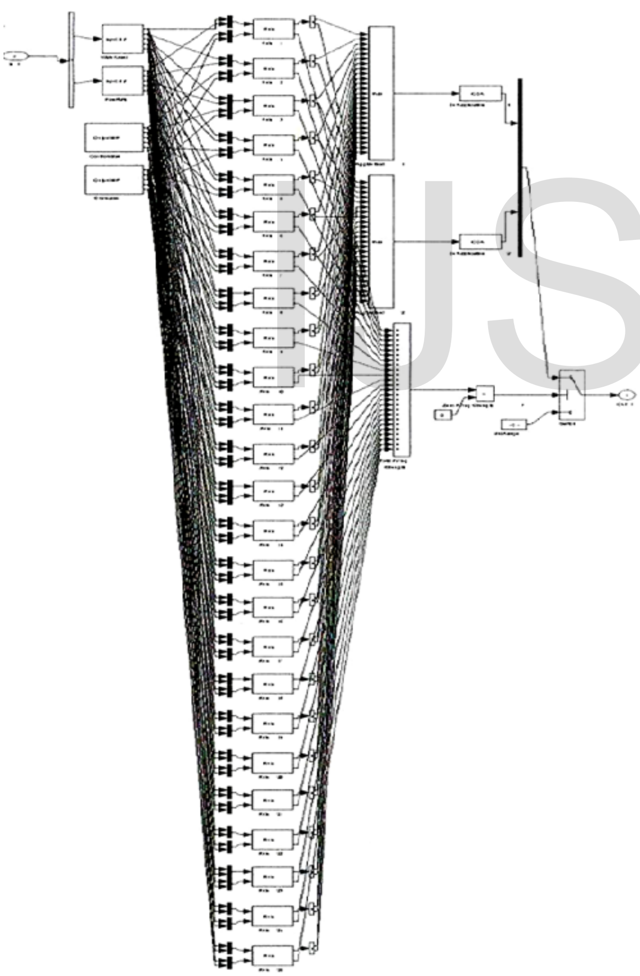


Figure 21: The Designed Neuro Fuzzy Hydro power stability Rules

DATA PRESENTATION AND ANALYSIS

Fuzzy systems are very suitable for data/ knowledge representation (using IF-Then rules) as well as explanation and analysis of data. Even though fuzzy systems are great in presenting and explaining data, they do not have learning capability. On the other hand, neural networks have the many different learning algorithm but they are not so great when it comes to knowledge presentation. However, Neural network cannot really explain data which makes it crucial when it comes into prediction. A Neuro Fuzzy system is a homogenous hybrid intelligence system. Such system uses base fuzzy system and expert knowledge to present data and then it uses neural network in order to develop IF- THEN rule and adjust input/output membership function to improve the overall performance of the system.

Table 4. Design value for Water level membership function sand Range of input Variable

PARAM	Membership function (MF)	Ranges	Region Occupied
-404	***Above Danger***	0 - 10	0 - 1
-126273674	***Danger***	0 - 10	0 - 1
1.064 5.0649 .064	***Below Danger***	0 - 10	0 - 1
-2.897 .06217	***Low***	0 - 10	0 - 1
0.7522 .9892073	***Very Low***	0 - 10	0 - 1

The table above describes the design data for the input variable of water level, see fig. 14 for the analysis.

Table 5. Design value for Flow Rate membership functions and Range of input Variable

Membership function (MF)	***Ranges***	***Region***	***Panam***
Closed fast	0 - 10	0 - 1	-404
Close Slow	0 - 10	0 - 1	1.0004274
No Change	0 - 10	0 - 1	-3.9967 .996
Opened slow	0 - 10	0 - 1	1.8975 .899 .897
Opened fast	0 - 10	0 - 1	0.96159 .8822096

The table above describes the design data for the input variable of Flow rate, see fig. 15 for the method of design and analysis.

ISSN 2229-5518

Table 6. Design value for Release control Valve membership functions and Range of output Variable

Membership function (MF)	Ranges	Region	Panam
Closed fast	0 -10	2 - 1	-5368 -011752622
Close Slow	0 - 10	2 - 1	- 0.0042743996 7 .98
No Change	0 -10	2 - 1	4.72615137
Opened slow	0-10	2 - 1	-8.827938112
Opened fast	0 - 10	2 - 1	1.1971003212 1

The table above describes the design data for the input variable of Release control valve, see fig 17, for the method of design and analysis.

Table 7. Design value for Drain Valve membership function sand Range of input Variable

Membership function (MF)	Ranges	Region	Panam
Very slow	0 - 10	2 - 1	-346900913 .651
Slow	0 - 10	2 - 1	133449
Normal	0 - 10	2 - 1	326854171127
Fast	0 - 10	2 - 1	-6.3257 .7251364
Very fast	0 - 10	2 - 1	1.339 .95213

The table above describes the design data for the input variable of Drain valve, see fig. 16 for the method of design and analysis.

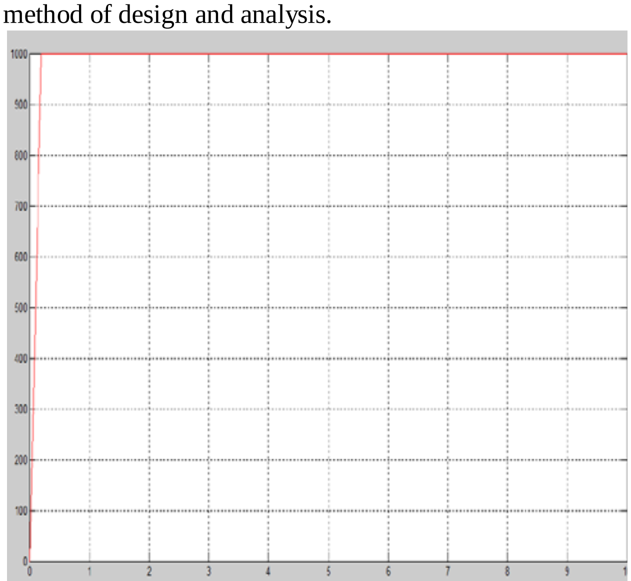
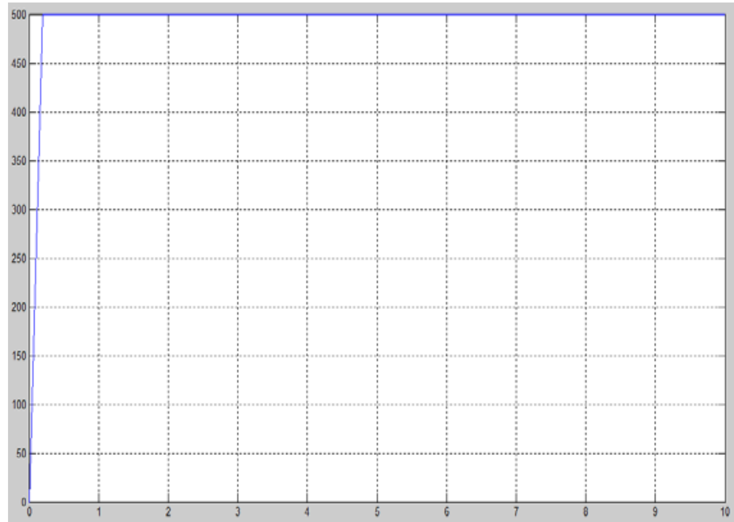


Figure 22: Graphical representation of the Output for release control valve



Time (s)

Figure 23: Graphical representation of the Output for drain valve

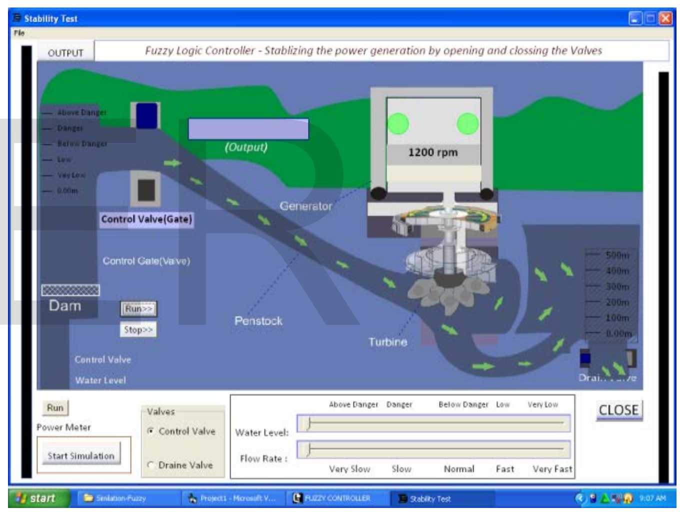


Figure 24: Visual representation of a designed Neuro- fuzzy Hydropower controller

Analysis of the Result

The analysis of the result presented above clearly demonstrates the ability of Neuro-Fuzzy scheme to significantly reduce the time necessary for dynamic security assessment. The real time controller emphasizes the robustness of Neuro-fuzzy application of scheme for steady state rotational stability for turbine spinning in a hydropower system .

Observation and Conclusion

The study presents the design of Neuro- fuzzy controller to regulate levels and control the flow through the valve (Penstock) to the turbine. As could be seen in the design, It starts from the theory until it is implemented into the simulation environment. Different numbers of rules that are used in the system were tested by using different membership functions. The results (error) observed from the conventional Fuzzy scheme is fed as an input to the cascaded neural network to achieve the desired output

REFERENCES

[1] Mahusudhana, G. Rao, Anwesha Kumar, B. V. Sankar Ram., Design of Neuro fuzzy Inference distributed power flow controller for transient stability improvement, Word Journal of Modeling and simulation, Vol. 10(2014) No. 4 pp. 252-260.

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

[3] Selwin Mich Priyadharson, M.S.Saravanan, N.Gomathi S. Vinson Josuah and A. Mutharasan Energy Efficient flow and level control in a hydr power plant using Fuzzy logic, Journal of Computer Science 10(9) 1703-1711, 2014.

[4] Arvind K Sharma, Gaurav Parwal, 2012, Neuro-fuzzy system based augmentation for transient Stability, international Journal of Advanced Research in Computer Science, Vol 3. No 6, Nov., 2012.

[5] Agus Jamal and Ramadoni Syahputra, 2012, Adaptive Neuro-fuzzy Approach for power system Stabilizer Model in Multi- Machine Power System, International Journal of Electrical &Computer Science Vol. 12 No: 02

[6] Chandra Shekar Besta1, Anil Kumar Kastala2, Prabhaker Reddy Ginuga3, Ramesh Kumar Vadeghar4, MATLAB Interfacing: Real-time Implementation of a Fuzzy Logic Controller Preprints of the 10th IFAC International Symposium on Dynamics and Control of Process Systems, International Federation of Automatic Control, December 18-20, 2013. Mumbai, India.

[7] Dharamniwas ans Aziz Ahmed, " Liquid Level control by using fuzzy logic controller, IJAET, July 2012, Vol. 4. Issue 1, pp, 532-549.

[8] Thae Ei Aung (2014), Design and Development of fuzzy logic Controller for flow of Dams IJCEM Vol. 17 Issue 3, May, 2014.

[9] Pratibha Srivastav, Manojjha, M.F. Qureshi, Co-Active Neuro- Fuzzy Inference System for Governing control and excitation Control of Power System Stability, international journal of Innovation Research in Science Engineering anf Technology, Vol.3, issue 6, June 2014.

[10] Malhotra, R,Singh, N., and Singh, Y., "An Effective Fuzzy- GA Flow Control of Turbine Compressor system: *International Journal of Advancements in Computing Technology, Vol. 2, No. 4 October, 2010.*

[11] Rahul Malhotra, Rajinder Sodhi"*fuzzy logic Boiler Flow Control using PID and Fuzzy logic controller" IJCSET, Vol. 1 Issue 6, pp 315- 319 2011.*

[12] *Mahusudhana, G. Rao, Anwesha Kumar, B. V. Sankar Ram., Design of Neuro fuzzy Inference distributed power flow controller for transient stability improvement, Word Journal of Modeling and simulation, Vol. 10(2014) No. 4 pp. 252-260.*

[13] *Mahusudhana, G. Rao, Anwesha Kumar, B. V. Sankar Ram., Design of Neuro fuzzy Inference distributed power flow controller for transient stability improvement, Word Journal of Modeling and simulation, Vol. 10(2014) No. 4 pp. 252*