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EXCITATION CONTROL OF SYNCHRONOUS GENERATOR USING NEURAL NETWORK

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***Abstract*—** Advanced power systems are complex and non-linear, and their operation can change to a wide extent [1]. Synchronous generator is at core of power system, and it is necessary to maintain reliable operation throughout. This paper presents the excitation control of the synchronous generator with the application of a neural network-based controller. Ordinary excitation control strategies have a slower reaction to non-linearities happening within the excitation system [2]. Executing Neural Network based controller(NNC) decreases reaction time showing strong steadiness [3].. Terminal voltage and current is nourished to the input of neural network and is processed to give reference current as output which then is converted into reference voltage and is used to produce duty cycle of thyristor by comparing it with varying field current. The neural network-based controller will sense the deviation of voltage and based on necessities, give the gating command to thyristor valves and in this manner acting quickly to the dynamics of the power system.

Keywords*— *Excitation Control, Synchronous Machine, Response Time, Neural Network Based Controller, NNC

I. INTRODUCTION

One of the most significant strategies to improve power system stability and ensure the quality of electrical power it produces is synchronous generator excitation control. The excitation system's principal control function is to modify the field voltage in response to changes in the terminal voltage. It must be able to respond fast to a disruption, hence improving transient and tiny signal stability [4]. Excitation system control in generation control is done mainly to regulate generator voltage and reactive power output [5].

Practical methods for nonlinear control include the use of feedback loops to cancel plant nonlinearities [6]. The approximation of a non-linear system with a linearized model yields the application of adaptive control, where real-time measurements of the plant inputs are used, either to derive explicitly the plant model or design a controller based on this model (Indirect adaptive control), or to directly modify the controller output (direct adaptive control) [7]. Ordinary excitation control strategies have a slower reaction to non-linearities happening within the excitation framework. To enhance system response, excitation control of synchronous generators with the application of Neural Network Controller(NNC) has been proposed which can enhance stability during abnormalities. Executing NNC decreases reaction time showing strong steadiness.

II. EXCITATION SYSTEM

An excitation system is a system that provides the necessary field current to the synchronous machine's rotor winding. In other terms, an excitation system is one that is utilized to generate flux by flowing current through the field coil. The most important characteristics of an excitation system are reliability in all operating circumstances, ease of control, ease of maintenance, stability, and fast transient response. The level of excitation required is determined by the machine's load current, load power factor, and speed. Furthermore, in a power system, the excitation system's protective features enable the synchronous machines' rated capacity limits to be improved [8].

1.1 Types Of Excitation System

Generally, there are 3 types of excitation system as follows:

2.1.1 DC Excitation

This category's excitation system uses a dc generator as a source of excitation power and delivers current to the synchronous machine's rotor via a slip ring. The exciter can be powered by a motor or the generator shaft [9]. It can be self-excited or independently excited.

2.1.2 AC Excitation

An alternator and thyristor rectifier bridge are directly connected to the main alternator shaft in the AC excitation system [10].

2.1.3 Static Excitation

This type of system gives synchronous generator field winding with excitation current by employing slip rings.. Station batteries are as a rule utilized as extra control sources and the method is known as field flashing [11].

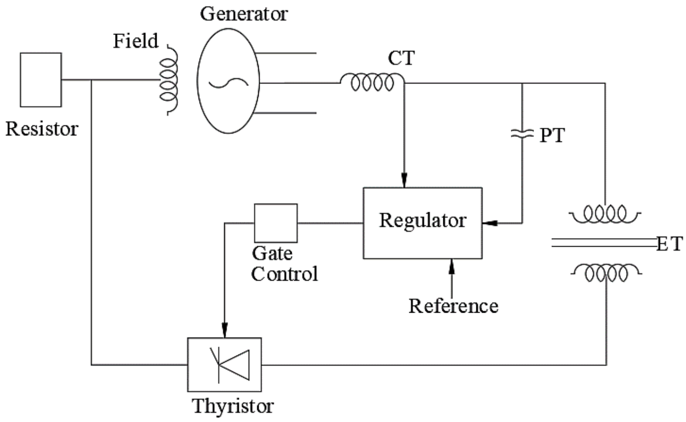

Figure 1: Static Excitation System

Excitation Transformer(ET) is employed to step down voltage and current to desired level. A thyristor network feeds the generator field. During generator faults, the field suppression resistor absorbs energy in the field circuit, while the field breaker guarantees field isolation.

1.2 Thyristor Valve(B6 connection)

A fully-controlled three-phase full-wave converter is made up of six thyristors coupled as illustrated in the diagram below. All six thyristors are controlled switches that are activated when appropriate gate trigger signals are applied [12]. The thyristor with the greatest positive voltage at its anode conducts when triggered in the three-phase full-wave regulated rectifier circuit, while the thyristor with the most negative voltage at its cathode returns the load current if triggered.

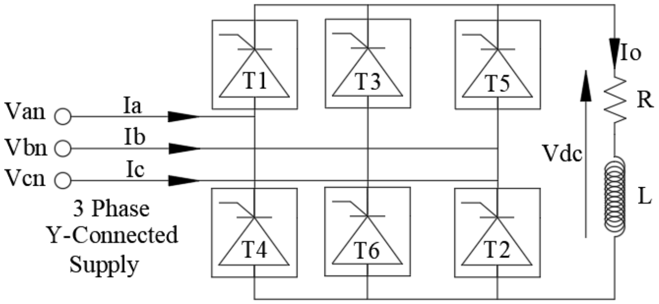

Figure 2: Phase Full Wave Controlled Rectifier

The average output voltage assuming continuous conduction and a strongly inductive load, can be calculated as follows.

$$V_{dc} = \frac{6\sqrt{3}}{\pi} V_m \sin\frac{\pi}{6} \cos\alpha = \frac{3\sqrt{3}V_m}{\pi} \cos(\alpha)$$

The output current is given by

$$I_{dc} = \frac{3\sqrt{3}V_m}{\pi R} \cos(\alpha)$$

Where:

V_{dc} is the average dc output voltage

V_m the maximum line to neutral voltage

α the firing angle of thyristor valve.

III. Artificial Neural Network

A neural network is a set of algorithms that attempts to detect underlying relationships in a batch of data using a method that mimics how the human brain works [13]. Neural networks can adapt to changing input, they can produce the best possible outcome without rewriting the output criteria. The artificial intelligence-based notion of neural networks is quickly gaining traction in the creation of trading systems [14].

The computing frameworks motivated by natural neural systems to perform diverse assignments with a colossal sum of information included are called Artificial Neural Network. Diverse calculations are utilized to get the connections in each set of information to create the leading that comes about from the changing inputs [15]. The network is prepared to create the specified yields, and diverse models are utilized to foresee the long haul that comes about with the information. The neurons are interconnected so that it works like a human brain.

Neural systems are prepared and instructed similarly to a child's creating brain is prepared [16]. They cannot be modified specifically for a specific assignment. They are prepared in such a way that they can adjust agreeing to the changing input.

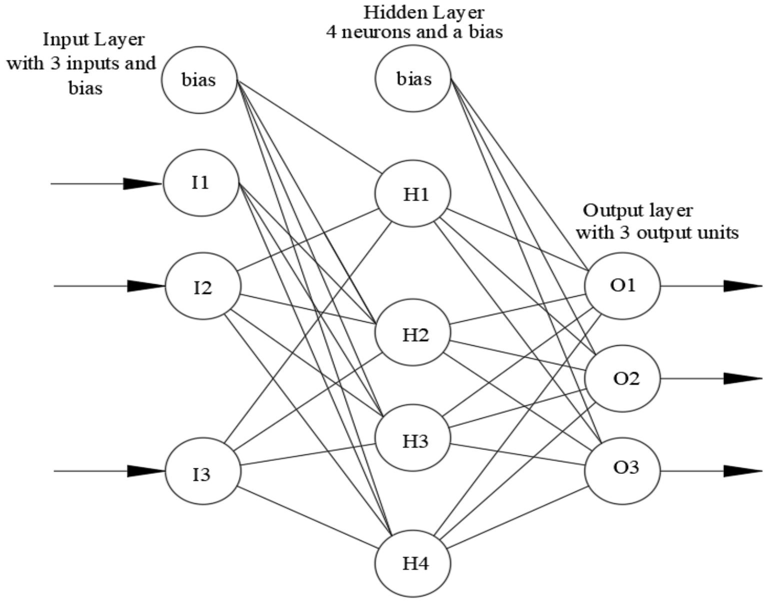

Figure 3: Structure of neural Network

A simple neural network consists of three components:

1. Input layer
2. Hidden layer
3. Output layer

Input Layer:

Also known as Input nodes, the inputs/information from the outside world is provided to the model to learn and derive conclusions. Input nodes pass the information to the next layer i.e Hidden layer.

Hidden Layer:

Hidden layer is the set of neurons where all the computations are performed on the input data. There can be any number of hidden layers in a neural network. These are connected by weights and biases The simplest network consists of a single hidden layer.

Output layer:

The output layer is the output/conclusions of the model derived from all the computations performed. There can be single or multiple nodes in the output layer.

Each input is duplicated by its particular weights and biases, and after that, they are activated. The values of weights determine the strength of signal and biases are constant values to provide better flexibility and generalization to the network [17]. The net activated inputs of the neurons are again activated when it goes out from the neurons.

Error is calculated between calculated and desired values. Error is reduced by updating values of weights and is limited by epochs to be performed. Epochs determine how many times the data's move back and forth in the network. There are different Activation Functions like Threshold function, Piecewise linear work, or Sigmoid function.

Mathematically, if MSE is used to determine the output:

$$\text{Activated Inputs} = \sum_{1}^{N} (\text{Inputs} * \text{Weights}) + \sum_{1}^{N} \text{bias}$$

Where N is number of inputs, weights and biases in the network

The output is given by:

$$\text{Calculated Output} = \text{Activation Function}(\text{Activated inputs})$$

The error is then calculated by:

$$\text{MSE} = \frac{1}{2}(\text{Desired Output} - \text{Calculated Output})^2$$

IV. METHODOLOGY

To perform the research work, it is started with identifying the main scope of the project and its related objectives. This is followed by reviewing of literary texts. Then, Neuro-controller is designed and result is analyzed.

For development of Neuro-controller, following flowchart for coding is used.

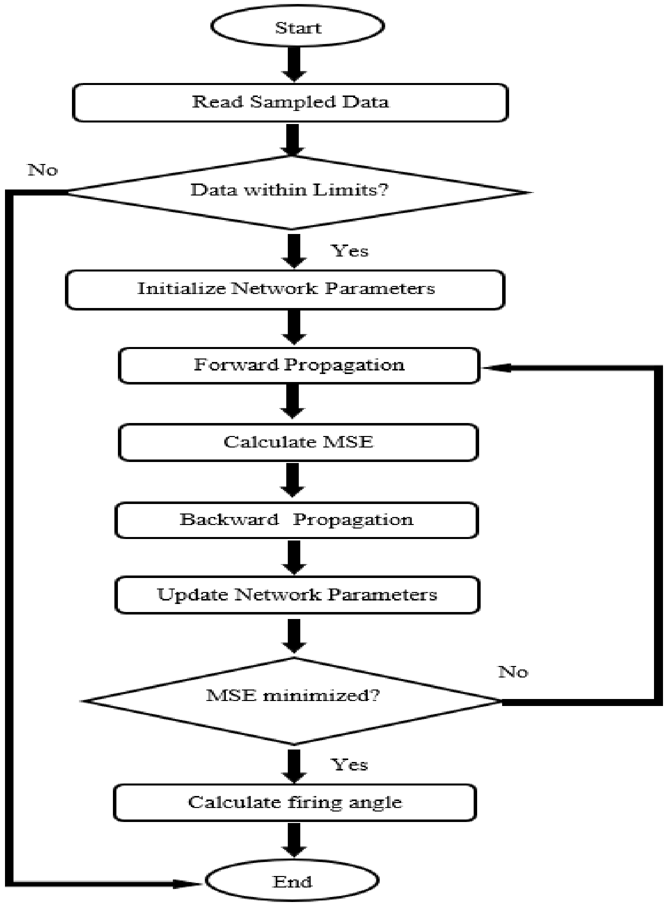

Figure 4: Flowchart for Coding

V. Development Of Neurocontroller

For development of NNC, the NNC and Generator parameters are given in following tables.

Table 1: NNC Parameters

Parameters	Values
Epoch	1000
Learning rate	0.8
No. of Inputs	2
No. of Hidden Layers	2
No. of Neurons In Hidden Layer 1	4
No. of Neurons In Hidden Layer 2	3
No. of Weights connecting Input & H1	8
No. of Weights connecting H1 & H2	12
No. of Weights connecting H1& Output	3

Table 2: Generator Parameter

Parameters	Values	Units
Rated power at UPF	200	MVA
Rated power at 0.9 PF lagging	220	MVA
Generator rated voltage	13.8	kV
Frequency	50	Hz
Terminal Voltage from ET	415	V
Field Voltage	250	V
Field Current	1270	A
Field Resistance	0.196850393	Ω
Upper Limit of Current	1333.5	A
Lower Limit of Current	1206.5	A

The implementation of NNC to generate duty cycle in synchronous generator excitation system is given below.

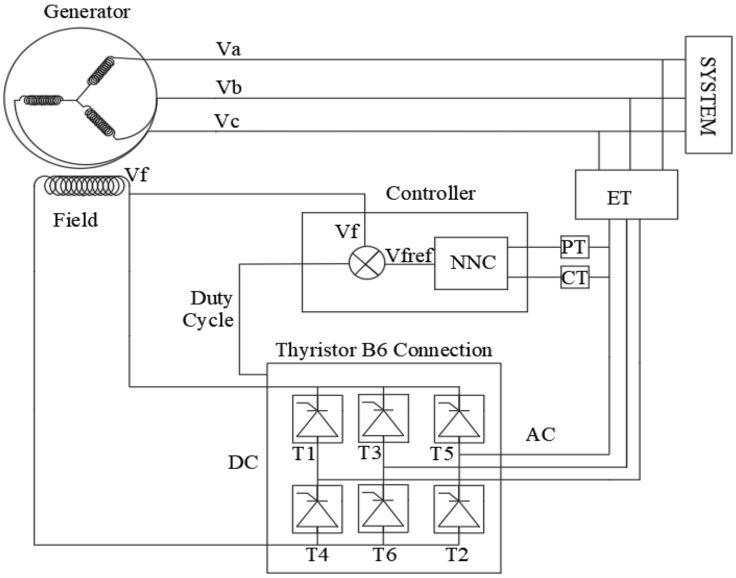

Figure 5: Schematic Diagram of Excitation Control Using NNC and B6 Thyristor Connection

For developing NNC, following neural network structure has been chosen. As depicted below, there are two inputs from the exterior system is sampled and fed to the network. Two hidden layers are chosen, and one output is taken from the network. There are 4 neurons in the first hidden layer and 3 neurons in the second hidden layer. The output is reference field current which is converted to reference field voltage and is compared with varying values of field voltage. The error in field voltage is converted into firing angle which is added and subtracted during increase and decrease in field voltage respectively.

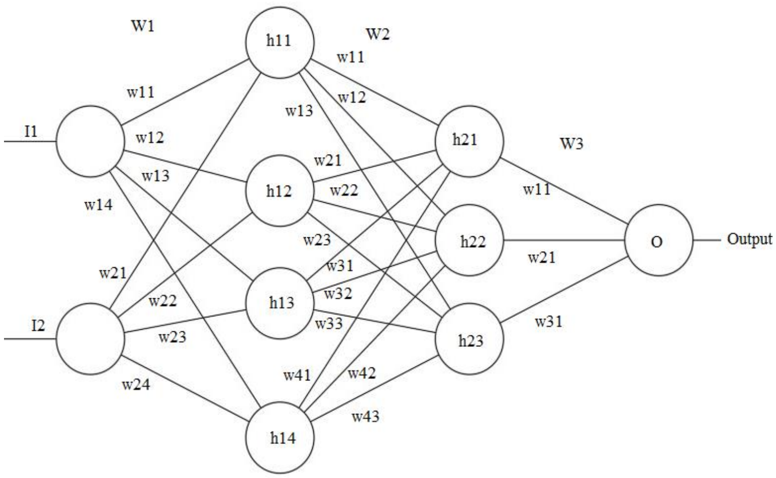

Figure 6: Neural Network Structure

The firing angle calculation of individual thyristors is given below:

$\alpha T1 = \alpha + 30^{\circ}$

$\alpha T2 = \alpha + 150^\circ$

$\alpha T3 = \alpha + 270^\circ$

$\alpha T4 = \alpha + 210^\circ$

$\alpha T5 = \alpha + 330^\circ$

$\alpha T6 = \alpha + 90^\circ$

Thyristors are fired at 60˚ depending on the crossover point of input AC voltage. The designed NNC will first check for limit violations. If input values are out of limit, NNC will display warning signals and execute without performing any operation. However provisions are there to operate the system beyond limits by displaying warning signal and executing the code.

VI. Result And Discussion

The MATLAB code was firstly executed at rated values of terminal voltage and current to calculate firing angle required to maintain output DC voltage of 250V. After calculating firing angle, input voltage and current values were varied within range of ±5% of rated value to study performance and response time of NNC. The response of NNC to various values of input voltage and current is given below.

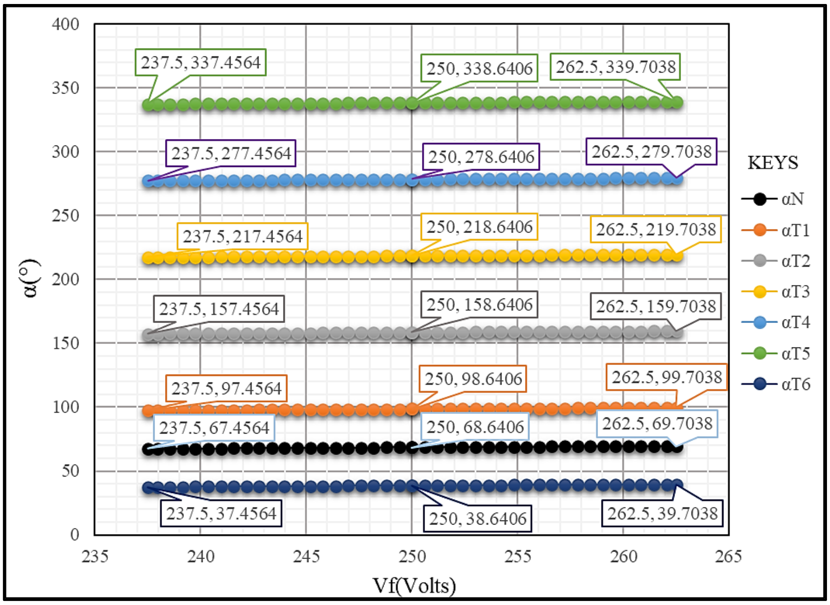

Figure 7: Variation Of Firing Instance Of All Thyristors With Varying Field Voltage

From Figure 7, the rated firing angle varies between 67.4564˚ to 69.7038˚ during variation in field voltage. This value is used for determining firing angle of all thyristors. To obtain 250V output voltage, T6 is fired at 38.6404 followed by T1, T2,T3, T4 and T5 with increase in 60˚ at each thyristors. Also, for single thyristor, firing angle varies within limits in relation to ±5% variation of terminal voltage. The lower limit of firing angle of thyristor T6 is 37.4564˚ with increase of 60˚ in following thyristors. The upper limit includes 39.7038 for thyristor T1 and increase by 60˚ in following thyristors. The average execution time of NNC was found to be 0.00186418s.

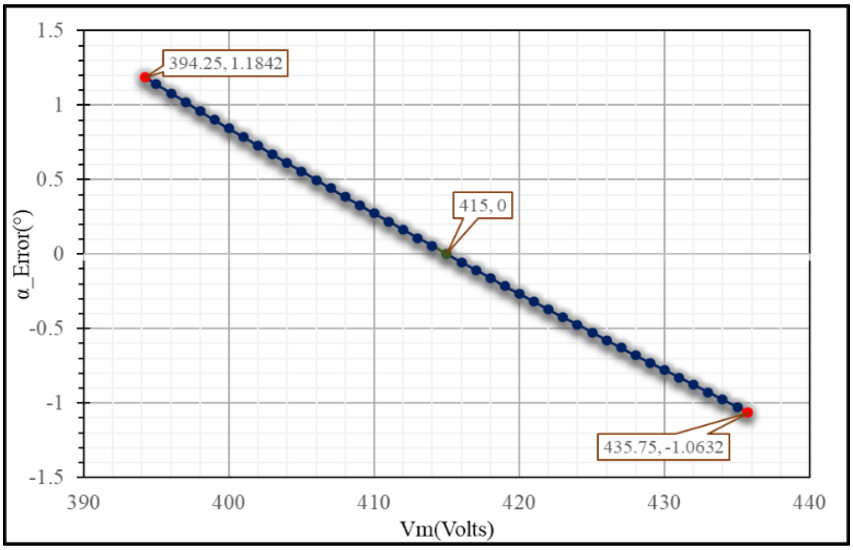

Figure 8: Variation Of Error In Firing Angle With Varying Terminal Voltage

From Figure 8, it can be observed that error is decreasing with increase in terminal voltage and is increasing with decrease in terminal voltage. Increase in error is depicting that firing angle has to be reduced to get desired output value of field voltage and vice versa. Error in firing angle at rated terminal voltage is 0 and during ±5% variation, it varies from -1.0632˚ to 1.1842˚ indicating that firing angle should be increased and decreased respectively. By doing so, output DC voltage is maintained at desired level.

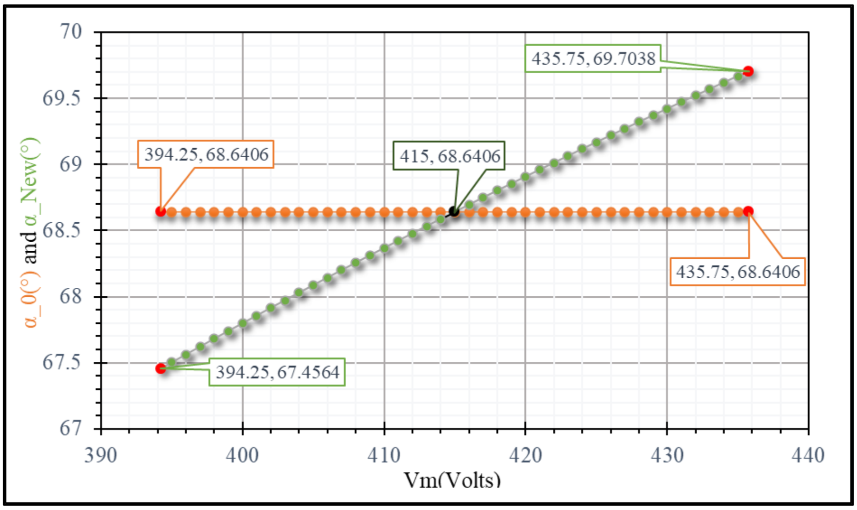

Figure 9: Variation Of New Firing Angle With Varying Terminal Voltage

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From Figure 9, at rated terminal voltage, rated firing angle is maintained. During 5% increase in terminal voltage, if firing angle is not change, it will result in 5% increased in field voltage and vice versa. To maintain rated output voltage, when there is +5% increase in terminal voltage, firing angle is increased from 68.6406˚ to 69.7038˚ thereby decreasing the magnitude of output voltage. Similarly, during 5% decrease in terminal voltage, angle decreased to 67.4564˚ from 68.6406˚ thereby maintaining constant output voltage.

For NNC, values of epoch and learning rate was varied to observe the variation in response time and NNC output.

From Figure 10, it can be observed that keeping epoch constant(1000), during variation of learning late, NNC output is also varied. At low values of learning rate, the calculated output of NNC is not same as the desired output. When learning rate increases, calculated output matches desired output. At learning rate of 0.4, desired output is attained.

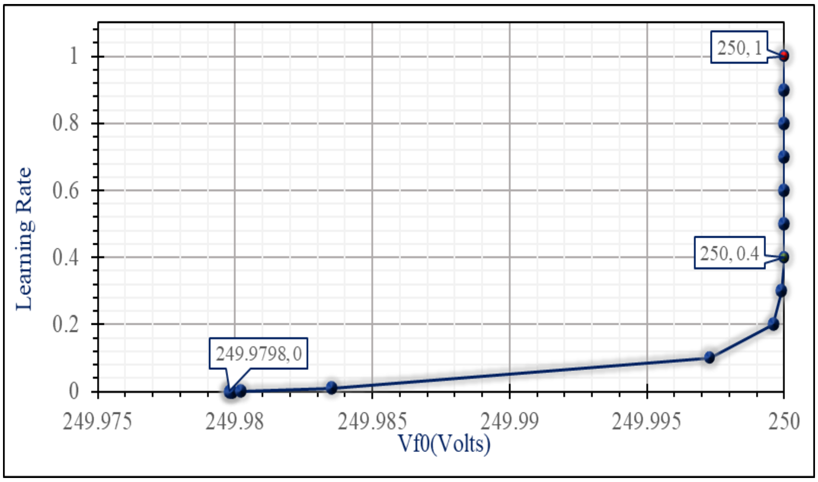

Figure 10: Response Of Output Voltage To Various Values Of Learning Rate

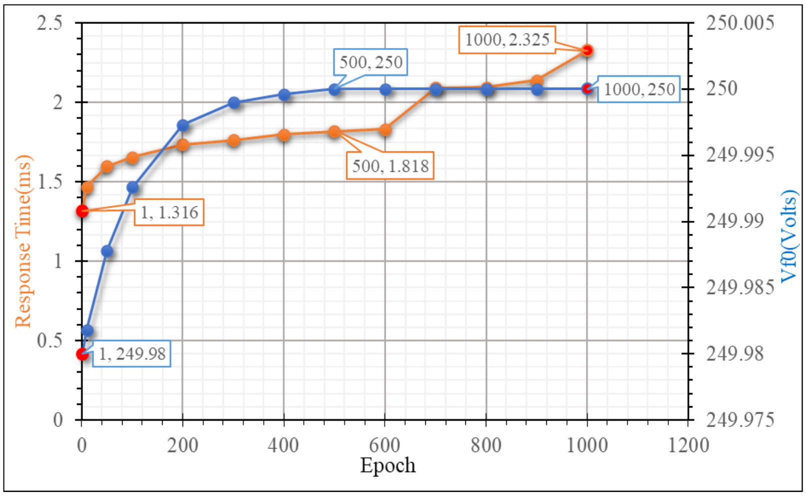

Figure 11: Variation Of Response Time And NNC Output With Varying Epoch

From above plot, it can be observed that keeping learning constant(0.5), at lower values of epoch, the response time of NNC is fastest but the NNC output is not at desired level. As epoch increases, NNC output is improved but response time is increasing too. The optimum value of epoch at `which NNC output matches desired output is 500 and corresponding response time is 1.818ms.

To determine the accuracy, comparison between the actual value of firing angle of thyristors and values obtained from NNC were compared. On average, the overall accuracy was found to be 99.9813%.

VII. CONCLUSION

Employing neural network to control excitation in synchronous generator is great approach as it reduces response time. By varying the firing angle through usage of NNC, it was possible to achieve desired field voltage to maintain excitation. During increase in terminal voltage, NNC as able to decrease field voltage to desired level by increasing firing angle and vice versa. The average response time was found to be 0.00182s during variation in terminal voltage which is indeed much faster than conventional controllers i.e, the average response time of AVR is 0.5s and PID controller is 0.1. However, it can vary during integration with digital control system where input values are sampled and fed to NNC and the output is converted to pulse timing by digital Pulse Width Modulator(PWM) controller.

Thus, from the findings, it is concluded that employing neural network based controller can sense the deviation of voltage and based on necessities, give the firing to thyristor valves and in this manner acting quickly to the dynamics of the power system.

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