Adaptive Learning and Control of Steam Turbine Brushless Excitation System Using Neuro Fuzzy

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Abstract – Many power generation plants in the pulp and paper industry are faced with high maintenance and down time due to the excitation system. In this project the design and simulation of a Neuro-fuzzy based voltage controller for regulating the output voltage of a synchronous generator is carried out. An automated Neuro-fuzzy logic based control strategy is presented for controlling the armature voltage of the synchronous generator by varying its field voltage. The controller makes an intelligent decision on the amount of field voltage that should be applied to the generator in order to keep the output voltage at its rated value. The control algorithm is implemented in MATLAB. The performance of the Neuro-fuzzy logic controller is compared with a conventional PI controller and also a fuzzy logic controller (FLC). It is observed that Neuro-fuzzy logic controller gives better performance than either of the two controllers.

Index Terms – Neuro-fuzzy based voltage controller, Synchronous Generator, MATLAB, Fuzzy Logic Controller (FLC).

1. INTRODUCTION

Synchronous generators are used extensively for a wide range of electricity generation applications. A range of power generation probably greater than for any other class of rotating electrical machines. On the lower end are the smaller machines for clock, timing and control application in the milliwatt range, at the higher end are giant alternators used in electric power generation i.e. 50-150 MW range.

Synchronous generators are responsible for the bulk of electrical power generated in the world today. They are mainly used in power stations and are predominantly driven either by steam or hydraulic turbines. More than 90% of electric energy used in the world is generated by alternators. The very large amount of energy generated by these generators has made companies very conscious about their efficiency. If efficiency of a 1000MW generating station improves by only 1%, it represents extra revenues of several hundred dollars per day.

Synchronous generators are usually connected to an infinite bus where the terminals voltage is held at a constant value by the momentum of all the generators also connected to it. Another common application of synchronous generators is their use in stand alone or isolated power generation systems. The voltage regulation (that is the voltage rise at the terminals when a given load is thrown off, the excitation and speed remaining constant), is of a critical importance in such type of generators.

The voltage regulation system in a standalone synchronous generator is called an automatic voltage regulator (AVR). It is a device that automatically adjusts the output voltage of the generator in order to maintain it at a relatively constant value. This is achieved by comparing the output voltage with a reference voltage and from the difference (error), it makes the necessary adjustments in the field current to bring the output voltage closer to the required value. Older AVR's used in early days belong to a class of electromechanical devices. They are generally slow acting and possess zones of insensitivity called dead bands. There is a wide variety of electromechanical AVR's ranging from vibrating contact regulators to carbon pile regulators. However, they are now being replaced with continuously acting electronic regulators.

The aim of this project is to develop an improved control system for steam turbine driven stand alone synchronous generator set. Its primary objective is to design and build a working prototype that incorporates a new control strategy and the latest engineering innovations. The objectives include ensuring that the prototype system

- Can be used effectively as a starting point for further studies into a new generation of controllers for stand alone synchronous generator sets.
- Incorporates a certain amount of artificial intelligence such that it is flexible and not specific to a particular type of engine-generator set
- Is designed using a systematic process which enables rapid prototyping of future improvements

- Takes advantage of modern digital electronic technology

2. NEURO-FUZZY LOGIC CONTROLLER

There are two types of fuzzy inference systems that can be implemented in the fuzzy logic applications: Mamdani-type and Sugeno-type. These two types of inference systems vary somewhat in the way outputs are determined.

One of the most important and difficulty which involved in FL is making decision about its appropriate parameters. For example, the parameters that should be attention and play an important rule in FL ability are membership functions, distributions of MFs, the fuzzy rules composition. Trial and error is one of the methods which by using it the parameter selection would be done. Furthermore, user's experience is one of the parameters that could have an effect on FL modeling. Therefore, all of these problem and lack of knowledge and time lead us to combine both neural networks and fuzzy logic to minimize the error and reach the optimized and better decision about the FL parameters. Fig.1. Shows the proposed model of excitation control system

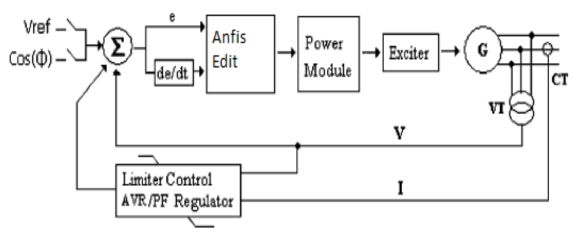

Figure 1 Excitation control system

3. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

The ANFIS is the abbreviated of *adaptive neuro-fuzzy inference system*. Actually, this method is like a fuzzy inference system with this different that here by using a backpropagation tries to minimize the error. The performance of this method is like both ANN and FL. In both ANN and FL case, the input pass through the input layer (by input membership function) and the output could be seen in output layer (by output membership functions). Since, in this type of advanced fuzzy logic, neural network has been used, therefore, by using a learning algorithm the parameters have been changed until reach the optimal solution. Actually, in this type the FL tries by using the neural network advantages to adjust its parameters. As we know, the different between real and network output in ANN is one of the common method to evaluate its performance. Therefore, ANFIS uses either backpropagation or a combination of least squares estimation and backpropagation for membership function parameter estimation.

4. METHODOLOGY

Over the past few years, the use of fuzzy set theory, or fuzzy logic, in control systems has been gaining widespread popularity. Fuzzy logic is a part of artificial intelligence (AI) which is an important branch of computer science. Recently AI techniques are making a serious impact in electrical engineering, particularly in the area of power electronics and motor drives. AI is basically computer emulation of human thinking called computational intelligence. The human brain is the most complex machine on earth. However, our understanding of the brain and its behavior has been extremely inadequate. The goal of the AI is to mimic human intelligence so that the computer can think like a human being. However complex the human thought process, there is no denying the fact that computers have adequate intelligence to help solve problems that are difficult to solve by traditional methods.

AI techniques are principally classified into four areas

- FUZZY LOGIC
- EXPERT SYSTEM
- ARTIFICIAL NEURAL NETWORK
- GENETIC ALGORITHM

Despite having similar objectives, the four techniques are profoundly different in both structure and performance. The difference essentially lies in the way that knowledge is represented in the system and how it is obtained.

The comparisons of the various intelligent systems are summarized in the table given in Table.1.

Properties	**Fuzzy systems**	**Expert systems**	**Neural networks**	**Genetic algorithms**
Mathematical model	Moderately good	Moderately bad	Bad	Bad
Learning ability	Bad	Bad	Good	Moderately bad
Knowledge representation	Good	Good	Bad	Bad
Expert knowledge	Good	Good	Bad	Bad
Knowledge acquisition	Bad	Bad	Good	Moderately good

Nonlinearity	Moderately good	Bad	Good	Good
Fault tolerance	Good	Bad	Good	Good
Uncertainty tolerance	Good	Bad	Good	Moderately good
Real time operation	Good	Bad	Moderately good	Bad
Explanation	Good	Good	Bad	Bad

Table.1. Comparisons of various intelligent systems

Control that is based on AI techniques is often defined as intelligent control. Traditional control is based on the mathematical models of the plant. For example, the control parameters of PI or PID control for linear system can be determined by Nyquist or Bode analysis. Intelligent control, on the other hand may not need any mathematical model. Many processes, such as nuclear reactor control, combustion in a boiler, chemical fermentation, etc, do not have mathematical models, or models may be ill defined. Even a well defined plant such as dynamic model of an induction motor may have parameter variation. Intelligent control is a good candidate for such plants.Today fuzzy logic based control systems or simply *fuzzy logic controllers* (FLCs), can be found in increasing number of products, from washing machines to speed boats, from air conditioning units to hand-held auto focus cameras.

The concept of fuzzy logic (FL) was conceived by Lotfi Zadeh, a professor at the university of California, Berkley. He presented it not as a control methodology, but as a way of processing data by allowing partial set membership rather than crisp set membership or non membership. This approach to set theory was not applied to control systems until the 70's due to insufficient small computer capability prior to that time. If feedback controllers could be programmed to accept noisy, imprecise input, they would be much more effective and perhaps easier to implement. Unfortunately, US manufacturers have not been so quick to embrace this technology while the Europeans and Japanese have been aggressively building real products around it.

The success of fuzzy logic controllers is mainly due to their ability to cope with knowledge presented in linguistic form instead of representation in the conventional mathematical framework. Control engineers have traditionally relied on mathematical models for their designs. However, the more complex a system, the less effective the mathematical model. This is the fundamental concept that provided the motivation for fuzzy logic .

Zadeh summarized that:

As the complexity of a system increases, our ability to make precise and yet significant statements about its behavior diminishes until a threshold is reached beyond which precision and significance become almost mutually exclusive characteristics

Real world problems can be extremely complex and complex systems are inherently fuzzy. The main advantage of fuzzy logic controllers is their ability to incorporate experience, intuition and heuristics into the system instead of relying on mathematical models. This makes them more effective in applications where the existing models are ill defined and not reliable enough.

5. HOW FUZZY LOGIC IS DIFFERENT FROM CONVENTIONAL CONTROL METHODS

Fuzzy Logic incorporates a simple, rule-based IF X AND Y THEN Z approach to solving control problems rather than attempting to model the system mathematically. The FL model is empirically based, relying on an operator's experience rather their technical understanding of the system. For example rather than dealing with temperature control in terms such as "SP=500F", "T<1000F", terms like "IF (process is too cool) AND (process is getting colder) THEN (add heat to the process)" or "IF (process is too hot) AND (process is heating rapidly) THEN " (cool the process quickly)" are used. These terms are imprecise and yet very descriptive of what must actually happen. FL's approach to control problems mimics how a person would make decisions, only much faster. It is robust and forgiving of operator and data input and often works when first implemented with little or no tuning.

5.1 WHY TO USE FUZZY LOGIC

FL offers several unique features that make it a particularly good choice for many control problems.

- It is inherently robust since it does not require precise, noise-free inputs and can be programmed to fail safely if a feedback sensor quits or is destroyed. The output control is a smooth function despite a wide range of input variations.
- Since FL controller processes user-defined rules governing the target control system, it can be modified and tweaked easily to improve or drastically alter system performance. New sensors can easily be incorporated into the system simply by generating appropriate governing rules.
- FL is not restricted to a few feedback inputs and one or two control outputs, nor is it necessary to measure or compute rate of change parameters in order for it to be implemented. Any sensor data that provides some indication of a system's actions and reactions is sufficient. This allows the sensors to be inexpensive

and imprecise thus keeping the overall system cost and complexity low.

- FL can control nonlinear systems that would be difficult or impossible to model mathematically. This opens doors for many control systems that would normally be deemed unfeasible for automation.

5.2 LINGUISTIC VARIABLES

The concept of linguistic variable, a term which is used to describe the inputs and outputs of FLC, is the foundation of fuzzy logic control systems. A conventional variable is numerical and precise. It is not capable of supporting the vagueness in fuzzy set theory. By definition, a linguistic variable is made up of words, sentences or artificial language which is less precise than numbers. It provides the means of approximate characterization of complex or ill defined phenomena. For example 'AGE' is a linguistic variable whose values maybe fuzzy sets, 'YOUNG' and 'OLD'.A more common example in fuzzy control would be the linguistic variable 'ERROR', which may have linguistic values such as 'POSITIVE', 'ZERO' and 'NEGATIVE'.

5.3 FUZZY LOGIC CONTROL

Figure 2 shows the block diagram of a typical fuzzy logic controller (FLC)and the system plant. There are five principal elements to a fuzzy logic controller:

- Fuzzification Module (Fuzzifier)
- Knowledge Base.
- Rule Base.
- Inference Engine.
- Defuzzification Module (Defuzzifier).

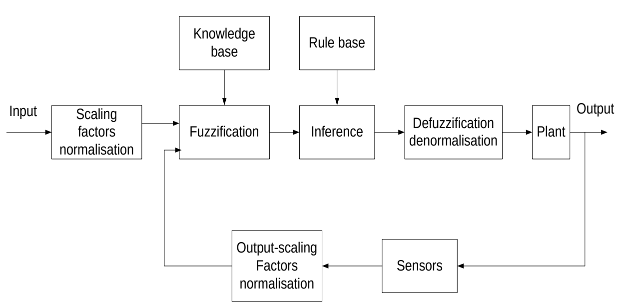

Figure 2 Block diagram of a typical fuzzy logic controller

Automatic changes in the design parameters of any of the five elements creates an adaptive fuzzy controller. Fuzzy control systems with fixed parameters are non-adaptive. Other non-fuzzy elements which are also part of the control system include the sensors, the analog-digital converters, the digital-analog converters and the normalization circuits. There are usually two types of normalization circuits: one maps the physical values of the control inputs onto a normalized universe of discourse and the other maps the normalized value of the control output variables back onto its physical domain.

Hence the fuzzy control algorithm realizing the control law is called PD like FLC.

NL: Negative large

NM: Negative medium

NS: Negative small

ZE: Zero

PS: positive small

PL: positive large

The exact shape of the fuzzy sets defined above is not of major concern. Although this is not a rule, in practice, the quantitizing fuzzy sets are usually symmetric triangles or trapezoids centered about representative values. This is not a rule though. The essence of fuzzy systems is the overlap between sets.

Voltage control rules are triples such as (NM, ZE, PM) where, NM and ZE correspond to the sets for error and del_voltage respectively, while PM corresponds to the set for field voltage. These rules describe how to modify the control variable for observed values of state variables. The voltage control is a 7 by 7 matrix with linguistic fuzzy sets entries. The columns of the matrix are indexed by the seven fuzzy sets that quantize the error universe of discourse .On the other hand, the rows are indexed by the seven fuzzy sets that quantize the 'del-voltage' universe of discourse.

Each matrix entry can equal one of the seven field voltage fuzzy set values. Also, for every pair of 'error' and 'del_voltage' values, there is exactly one 'field voltage 'value. Common sense and a certain amount of experience is used in obtaining the entries for a matrix. For example, if the voltage does not change, the del_voltage=ZE. Now, if 'error' is a positive value, then the value of 'field voltage' must be negative. Therefore the fourth row corresponding to 'del_voltage=ZE' should be equal the ordinal inverse of 'error' as shown in the Table.5.2 and Figure 5.1 shows the membership functions of input and output variables

	Change in Voltage Error c(kT)										
Voltage Error e(kT)	NV	NL	NB	NM	NS	ZR	PS	PM	PB	PL	PV
NV	NV	NV	NV	NV	NV	NV	NL	NB	NM	NS	ZR
NL	NV	NV	NV	NV	NV	NL	NB	NM	NS	ZR	PS
NB	NV	NV	NV	NV	NL	NB	NM	NS	ZR	PS	PM
NM	NV	NV	NV	NL	NB	NM	NS	ZR	PS	PM	PB
NS	NV	NV	NL	NB	NM	NS	ZR	PS	PM	PB	PL
ZR	NV	NL	NB	NM	NS	ZR	PS	PM	PB	PL	PV
PS	NL	NB	NM	NS	ZR	PS	PM	PB	PL	PV	PV
PM	NB	NM	NS	ZR	PS	PM	PB	PL	PV	PV	PV
PB	NM	NS	ZR	PS	PM	PB	PL	PV	PV	PV	PV
PL	NS	ZR	PS	PM	PB	PL	PV	PV	PV	PV	PV
PV	ZR	PS	PM	PB	PL	PV	PV	PV	PV	PV	PV

Table.2. Rule base for fuzzy controller

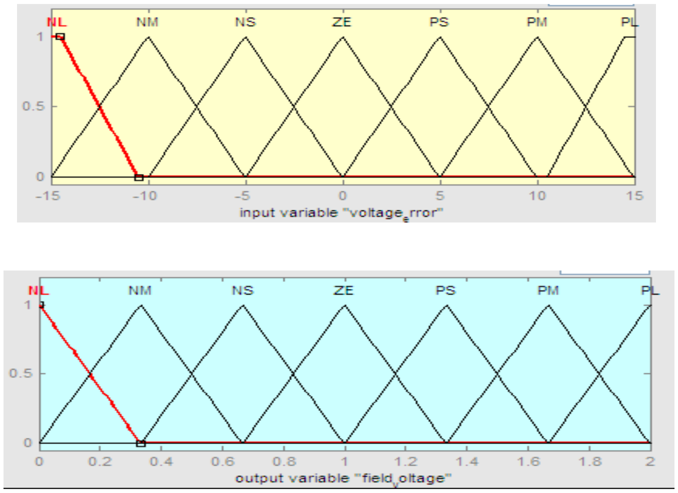

Figure 3. Membership functions (a) del_voltage (b)Voltage error(c) field voltage

6 ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

Adaptive Neuro Fuzzy Inference System (ANFIS) is a fuzzy mapping algorithm that is based on Tagaki fuzzy inference system. ANFIS is integration of neural networks and fuzzy logic and have the potential to capture the benefits of both these fields in a single framework. ANFIS utilizes linguistic information from the fuzzy logic as well learning capability of an ANN for automatic fuzzy if-then rule generation and parameter.

6.1 ANFIS EDITER

Fig.4. shows the anfis GUI (Graphical User Interface)

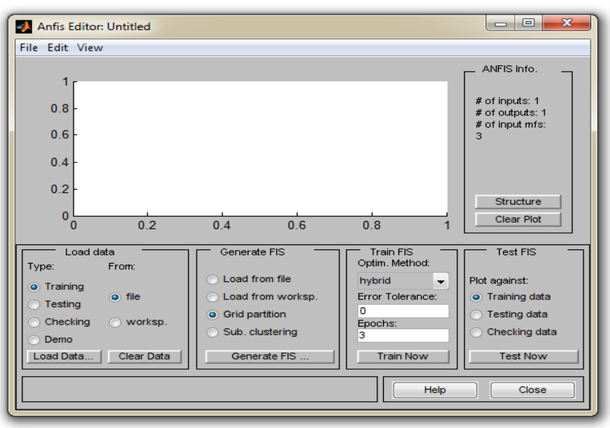

Figure 4. Anfis GUI (Graphical User Interface)

It is possible to use a graphical user interface

- Command anfisedit.
- It is possible to use the command line interface or m-file programs.
- There are functions to generate, train, test and use these systems.

7 ARTIFICIAL NEURAL NETWORK (ANNS):

McCulloch and Pitts were the first persons who introduced a model of an elementary computing neuron and six years later, Hebb proposed learning rules. ANNs have seen a rapid growth (after back propagation) and it has been applied widely in many fields ANN could to extend its applications such as pattern classification, function approximation, identification purpose for linear or nonlinear, multivariable systems. A simple NN has been composed of neurons, links which connects the neurons and weights that assigned to neurons and the bias which assigned to neurons. The nature of NN is made of mathematical equations which mimic the brain. Since, NN is made up several neuron and different layers; therefore, it would be possible to perform the massive parallel computation (Fig.5.)

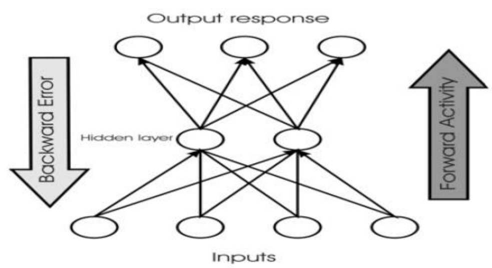

Figure 5. A Multi-Layer Back-Propagation (BP) Network with One Layer of Hidden Units

The position and the different neuron connection lead to have several NN and classified in the different groups. These groups could be such as feed forward network (e.g. single layer perceptron, multilayer perceptron and radial basis function), recurrent-feedback networks (competitive networks, Kohonen's SOM, Hopfield network and ART models). All of these structures have their specific applications. There are several training algorithms which each of them has their specific advantages and disadvantages but back propagation that is based on error backward and its correction is the most popular one. Actually, this algorithm is based on gradient descent method which according to error surface tries to find the best weight and bias composition in order to minimize the network error .

There are two important processes in BP algorithm: the input passed through the layers and neurons and the error will be calculated then, according to error the input will be backward propagation to adjust weights. However, this method has some disadvantages like slow converges, lack of robustness and inefficiency

Therefore, several contraptions such as adaptive method and second order method of modification have been proposed to achieve the better training and less error. One of the most successful methods which could to improve the training process is Levenberg-Marquardt (LM) that is a method which is based both Gauss-Newton nonlinear regression and gradient steepest descent method.

8 TRAINING OF ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

Trining of neuro-fuzzy have several steps. At the first step of training, the initial fuzzy sets should be determined. Actually the fuzzy sets define the number of sets for each input variable and their shapes. The not that should be attention is that large number of sets may produce better fitness in training process but a poor validation Therefore, to avoid from these problems, after several experiments, we selected 5 sets for each input variable. During training, all of the training dataset would be present to network and it tries by learning the spatial relationship between the data to minimize the error. Sometime lower error could not guaranty the better performance of network and it may because of network overtraining.

There is need to monitor how well the network is learning.

It is important to mention that when the input pass through the network, the aim of the ANN is to by parameters adjusting lead the network to the smallest error "as much as possible". Therefore, by error monitoring of training dataset, it would be possible to supervise on network training. The objective function which has been used here is MES (Mean Square Error). Definitely, the aim of using this network or the entire models is to reach the smallest error and also it is true here. Another way to an accurate solution is to set a criterion to stop the training phase that the goal of the stop criterion is to maximize the network's generalization. Currently, the training is based on 50 epochs which is using the hybrid learning algorithm.

8.1 ANFIS STRUCTURE

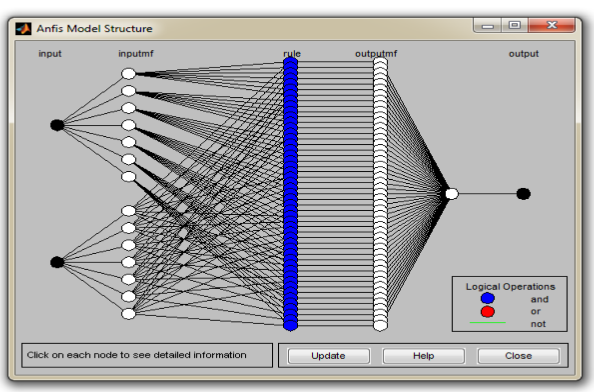

Figure 6. Adaptive Neuro-Fuzzy Structure

As mentioned earlier, seven bell-typed fuzzy membership functions were selected to describe the input and output variables. This is translated in 7^2 =25 rules (regarding the two inputs with seven fuzzy 2 sets each) Fig.6. shows the Adaptive Neuro-Fuzzy Structure.

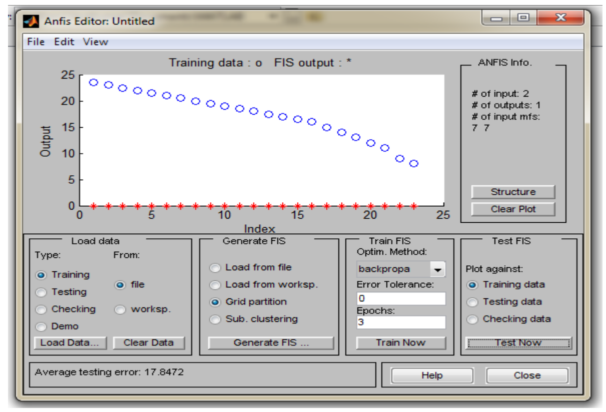

Figure 7. Before training anfis

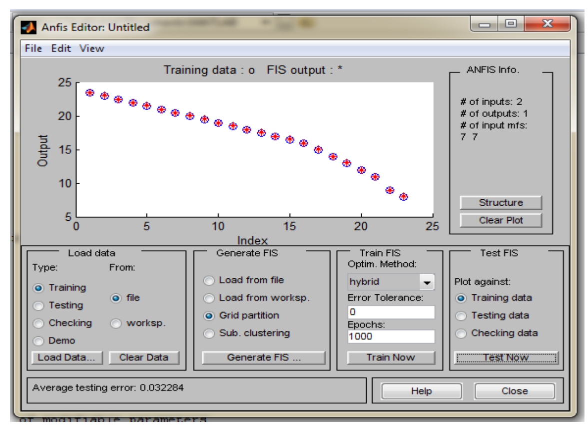

Figure 8. After training anfis

9 MATHEMATICAL MODELLING OF VOLTAGE CONTROLLER FOR THREE PHASE ALTERNATOR

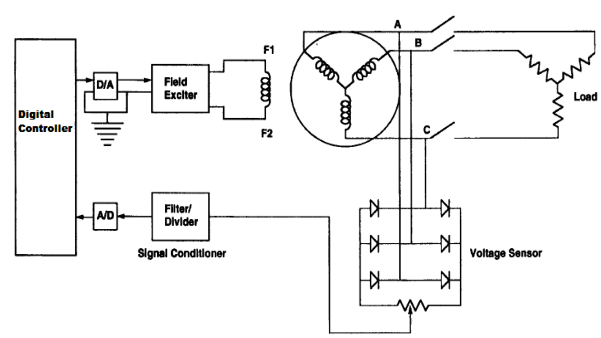

Figure 9. General schematic of the set up

The general schematic of the system is shown in Fig.9. It consists of a synchronous generator, the output voltage of which is rectified. This rectified voltage is then fed to the controller which compares the actual output with a reference voltage and based on the error, i.e., the voltage difference between the reference and the actual voltage and the rate of change of error, the controller takes an intelligent decision on the amount of field voltage to be applied to the generator so that the output voltage remains constant under varying load conditions.

10 MATHEMATICAL MODELLING OF SYSTEM FOR VOLTAGE CONTROL OF ALTERNATOR

The d-q equivalent circuit of the synchronous generator is shown in Fig.10.. The model is represented in the rotor reference frame (qd frame). All rotor parameters and electrical quantities are viewed from stator. They are identified by primed variables. The subscripts used are defined

- *d, q:* d and q axis quantity
- *R, s:* Rotor and stator quantity
- *l, m:* Leakage and magnetizing inductance
- *f, k:* Field and damper winding quantity

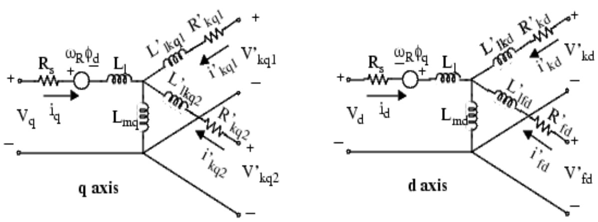

Figure 10. Electrical model of the synchronous generator

With the following equations

$$V_d = R_s i_d + \frac{d}{dt}\phi_d - \omega_R \phi_q \tag{1}$$

$$V_q = R_s i_q + \frac{d}{dt}\phi_q - \omega_R \phi_d \tag{2}$$

$$V'_{fd} = R'_{fd} i'_{fd} + \frac{d}{dt}\phi'_{fd} \tag{3}$$

$$V'_{kd} = R'_{kd} i'_{kd} + \frac{d}{dt}\phi'_{kd} \tag{4}$$

$$V'_{kq1} = R'_{kq1} i'_{kq1} + \frac{d}{dt}\phi'_{kq1} \tag{5}$$

$$V'_{kq2} = R'_{kq2} i'_{kq2} + \frac{d}{dt}\phi'_{kq2} \tag{6}$$

$$\phi_d = L_d i_d + L_{md}\left(i'_{fd} + i'_{kd}\right) \tag{7}$$

$$\phi_q = L_q i_q + L_{mq} i'_{kq} \tag{8}$$

$$\phi'_{fd} = L'_{fd} i'_{fd} + L_{md}\left(i_{fd} + i'_{kd}\right) \tag{9}$$

$$\phi'_{kd} = L'_{kd} i'_{kd} + L_{md}\left(i_d + i'_{fd}\right) \tag{10}$$

$$\phi'_{kq1} = L'_{kq1} i'_{kq1} + L_{mq} i_q \tag{11}$$

$$\phi'_{kq2} = L'_{kq2} i'_{kq2} + L_{mq} i_q \tag{12}$$

a. PI CONTROLLER

This is a control mode that results from a combination of the proportional mode and the integral mode. The main advantage of this composite control mode is that the integral mode eliminates the offset problem of proportional controllers. The mode can be used in systems with frequent or large load changes. The analytic expression for this control process is:

$$p = K_p e + K_I \int_0^t e dt \tag{13}$$

Where

K_P proportional gain

K_I integral gain

p controller output

e error

b. FUZZY LOGIC CONTROLLER

The fuzzy logic controller implemented in this project is PD in nature. The fuzzy PD controller describes with the aid of fuzzy if then rules, the relationship between the control value u(k) on one hand and the error e(k) and its change $\Delta e(k)=e(k)-e(k-1)$ on the other hand as

$$u(k)=F(e(k),\Delta e(k)) \quad (14)$$

the rules of this FLC have as inputs(antecedents), the error e and its change Δe and as output the control u.

the mapping in eq. 4.26 implemented in the FLC is similar to the known PD controller .

$$u(k)=K_p e(k)+K_D \Delta e(k)$$

11 SIMULINK - SIMULATION AND MODEL-BASED DESIGN

Simulink® is an environment for multi domain simulation and Model-Based Design for dynamic and embedded systems. It provides an interactive graphical environment and a customizable set of block libraries that let you design, simulate, implement, and test a variety of time-varying systems, including communications, controls, signal processing, video processing, and image processing.

KEY FEATURES

- Extensive and expandable libraries of predefined blocks
- Interactive graphical editor for assembling and managing intuitive block diagrams.
- Ability to manage complex designs by segmenting models into hierarchies of design components
- Model Explorer to navigate, create, configure, and search all signals, parameters, properties, and generated code associated with your model
- Application programming interfaces (APIs) that let you connect with other simulation programs and incorporate hand-written code
- Embedded MATLAB™ Function blocks for bringing MATLAB algorithms into Simulink and embedded system implementations
- Simulation modes (Normal, Accelerator, and Rapid Accelerator) for running simulations interpretively or at compiled C-code speeds using fixed- or variable-step solvers.
- Graphical debugger and profiler to examine simulation results and then diagnose performance and unexpected behavior in your design
- Full access to MATLAB for analyzing and visualizing results, customizing the modeling environment, and defining signal, parameter, and test data.
- Model analysis and diagnostics tools to ensure model consistency and identify modeling errors

A. MATLAB MODEL OF ALTERNATOR (SYNCHRONOUS MACHINE)

Figure.11. shows the MATLAB simulink model of Synchronous machine

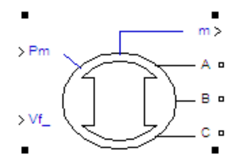

Figure 11. Synchronous machine model

The synchronous machine operates in generator or motor modes. The operating mode is dictated by the sign of the mechanical power (positive for generator mode and negative for motor mode).

12 RESULTS AND DISCUSSION

A. PERFORMANCE WITH PI CONTROLLER FOR EXCITATION CONTROL

The performance of the alternator is studied when a PI controller for excitation control is used which regulates the field voltage of the synchronous generator under various loading conditions. The generator is initially started with a load of 50MW and after t=1.5sec, an additional load of 50MW is put on the generator terminals. The output voltage of the synchronous generator is rectified through a bridge rectifier. This dc voltage is then stepped down and is compared with a reference value (195V). The error (change in voltage between the reference and the actual output voltage) and the integral of the error is calculated and the field voltage varies according to these two inputs. The various waveforms are shown in Fig.12.

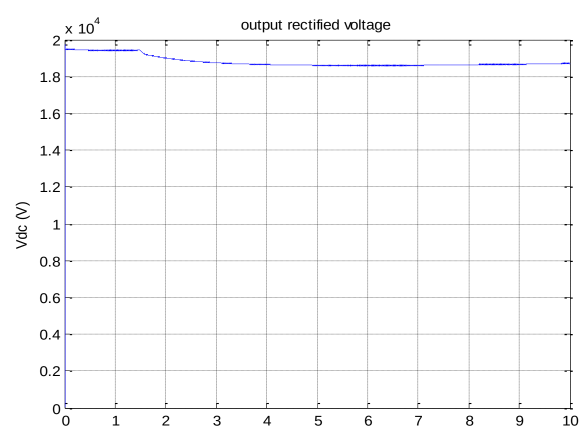

Fig.12. Rectified terminal voltage of synchronous generator

B. PERFORMANCE WITH NEURO-FUZZY LOGIC CONTROLLER (ANFIS) FOR EXCITATION CONTROL

The output voltage is now regulated by the neuro-fuzzy logic controller.

ANFIS info:

Number of nodes: 131

Number of linear parameters: 49

Number of nonlinear parameters: 42

Total number of parameters: 91

Number of training data pairs: 23

Number of checking data pairs: 0

Number of fuzzy rules: 49

Start training ANFIS.

1 0.0322838

2 0.0322842

Designated epoch number reached --> ANFIS training completed at epoch 2.

C. COMPLETE MATLAB MODEL OF A SYNCHRONOUS GENERATOR CONNECTED TO A TURBINE

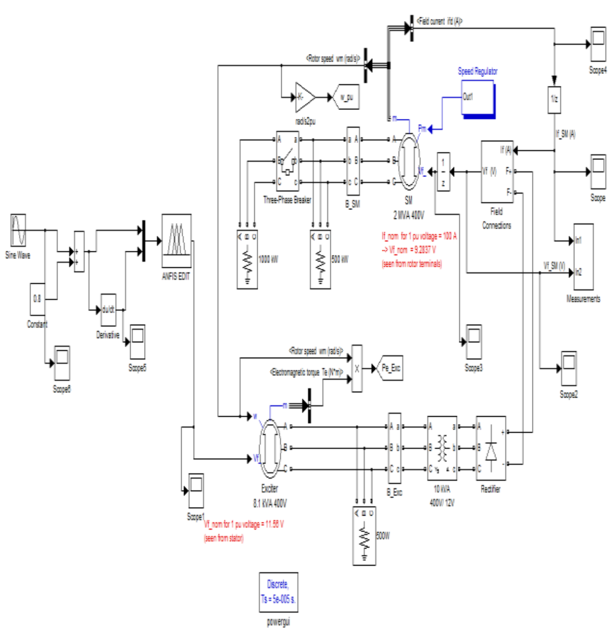

Figure 13. Complete MATLAB Model of a Synchronous Generator.

The output voltage is now regulated by the neuro-fuzzy logic controller. The rule base and the membership functions have been already described in the previous chapter. Neuro-fuzzy logic controller takes two inputs: the change in voltage and the rate of change of voltage and the output is the field voltage which varies according to the change in the two inputs.

The output voltage of the generator is rectified and compared with a reference which gives the error. The error is then passed through a derivative block which gives the rate of change of error. These two inputs go to the neuro-fuzzy logic controller which then takes an intelligent decision on the amount of field voltage to be applied based on these two inputs. . Fig.13. shows the synchronous generator connected to the ANFIS

Fig.14. shows the various waveforms when a load of 500KW is suddenly put on the generator terminals at t=1.5s.

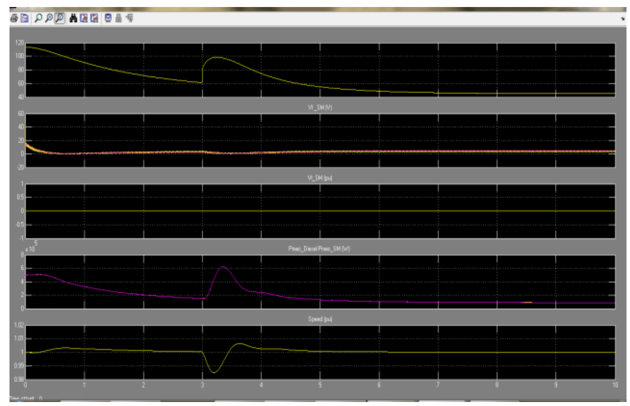

Figure 14. Performance of the alternator with neuro-fuzzy controller

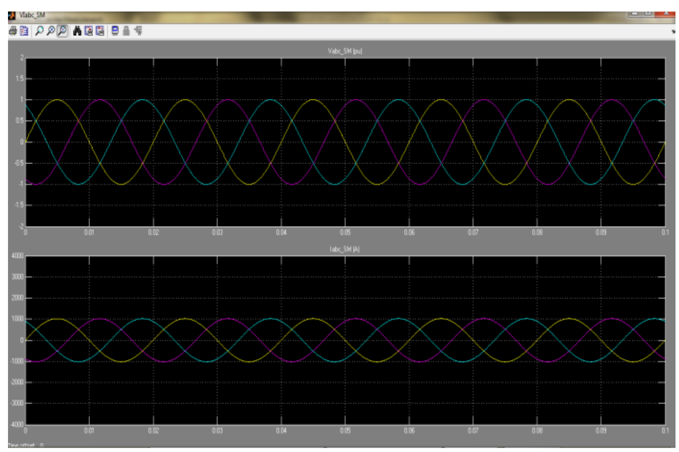

Figure 15. voltage waveforms generated across each phase

Fig.15. shows that the voltage waveforms generated across each phase are drawn on a graph, phase-displaced 120º from each other. The three-phase alternator as shown in this schematic is made up of three single-phase alternators whose generated voltages are out of phase by 120º . The three phases are independent of each other.

13 CONCLUSION

In this work, mathematical modeling and MATLAB simulation for voltage regulation through excitation control of synchronous generator is described in details. Different types of excitation controllers such as PI, FLC, and ANFIS have been used and simulation performance of the synchronous generator is obtained and analyzed in detail. A Neuro-fuzzy logic controller when used to regulate the output voltage of a synchronous generator under various loading conditions offers superior performances.

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