Neuro-Fuzzy Control of Single Machine Infinite Bus Power System

Abduladhem A.Ali [1] Abbas H.Abbas [2] Rasheed S.Jassim [3]

[1]College of Engineering, University of Basrah ,E-mail:abduladem@hotimal.com

[2]College of Engineering, University of Basrah, E-mail:abbashafeth@yahoo.com

[3]Basrah technical Institute,E-mail: a.fuzzy@yahoo.com

Abstract:

The excitation and governing control of generator play an important role in improving the dynamic and transient stability of power system. Typically the excitation control and governing control are designed independently. This paper, presented Neuro-Fuzzy methods for the excitation and governing control . Neuro-Fuzzy system is applied to generate two compensating signals to modify the controls during system disturbances. A single machine to infinite bus (SMIB) system is applied in simulation. The MATLAB SIMULIK and S-function technique is used to simulate the system and controllers

استخدام الخلايا العصبية المضببة للسيطرة على ماكنة منفردة مربوطة إلى قضيب عمومي

أ.د.عبد العظيم عبد الكريم علي
كلية الهندسة جامعةالبصرة
قسم هندسة الحاسبات

م.د.عباس حافظ عباس
كليةالهندسة جامعةالبصرة
قسم الهندسة الكهربائية

م.د.رشيد صباح جاسم
الكليةالتقنية بصرة
تقنيات القدرة

الملخص:

تلعب السيطرة والتحكم بالإثارة في مولدات القدرة الكهربائية دورا هاما في تحسين استقرارية منظومة القدرة بنوعيها الديناميكي والعابر. وفي الحقيقة فان السيطرة عليهما تتم بصورة مستقلة إحداهما عن الأخرى.

هذا البحث يقدم تمثيلا للسيطرة على الإثارة بواسطة الخلايا العصبية المضببة. تم تطبيق منظومة الخلايا العصبية المضببة لتوليد إشارتين تعويضيتين لتعديل السيطرة خلال حدوث اضطرابات بالمنظومة.وللتمثيل فقد تم استخدام ماكنة منفردة مربوطة إلى قضيب عمومي باستخدامتقنيات Simulink - Mathlab ودالة-S لتمثيل المنظومة والسيطرة عليها.

1- Introduction

Power system stability issue has been studied widely; many significant contributions have been made, not only in the aspects of analyzing and explaining the dynamic phenomena, but also in the efforts of improving the stability of transmission systems. Among these improvements, generator control is one of the most widely applied techniques in the power industry. This typically includes governing and excitation control. Most attenuation is directed towered the excitation control [1,2].

Many reports were published on application of the modern control theory to the generator control starting with, an optimal excitation control using Lyapunov's direct method and nonlinear system equation by (J.Machaws and et.al 1998)[3]. A decentralized control of a non-linear turbo-generator system using the Lyapunov's theory of stability the control structure is decentralized with simplified co-ordinate was presented in et.al [4]. Guo et.al in 1998 describes an application of nonlinear decentralized robust control to large-scale power system [5-7].An indirect adaptive non-linear control scheme for a power system is present by (Do.Kwau lee et.al[8]. Control algorithms based on Fuzzy and fuzz neural have been implemented in many researches [9-13].

2- Single-Machine-Infinite-Bus (SMIB) Model

Figure (1) gives the schematic diagram of load frequency and excitation model of Single-Machine-Infinite-Bus (SMIB) system.

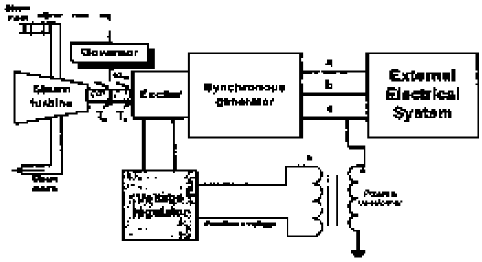


Fig.1 Schematic diagram of load frequency and excitation Model of SMIB Power System

2.1 <u>Exciter and voltage regulator model</u>

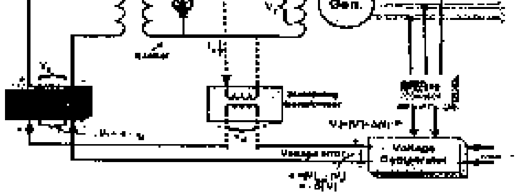
Figure(2-a) shown the excitation and voltage regulator model, and the block diagram of transfer faction of this model shown in fig (2-b).The original function of the exciter and voltage regulator is to provide the synchronous machine field winding with the adequate excitation such that the excitation increase for a voltage rises. Traditionally, a voltage error is defined by [1].

$$\Delta v_t = v_{Ref} - v_t \quad (1)$$

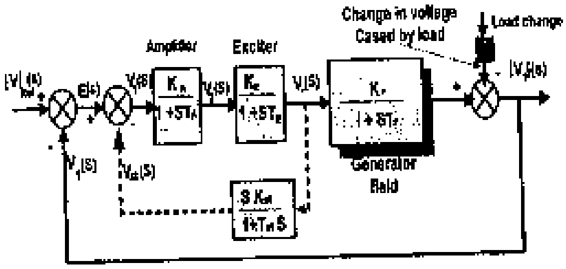
which is equivalent to

$$\Delta v_t = -(v_t - v_{Ref}) \quad (2)$$

That is and a negative feedback. In the above two equations, v_t represents the generator terminal voltage measured through an optional transforms rectified and filtered, and V_{Ref} is a reference voltage.



(a) Actual System



(b) Block diagram
Fig 2 Typical Exciter and Voltage Regulator

The original function of a governor is to maintain a constant speed of the prime mover by controlling the energy input using a speed deviation as the control feedback. The speed deviation is obtained by comparing the actual speed ω with a reference speed ω_{Ref},

$$\Delta \omega = \omega_{Ref} - \omega = -(\omega - \omega_{Ref}) \quad (3)$$

which is a negative feedback. The governor is so designed that a speed drop of prime mover below a reference level will bring about an energy increase, and a speed increase above a reference level will bring about an energy decrease. . Figure(3) shows the essential features of a speed governing system [2].

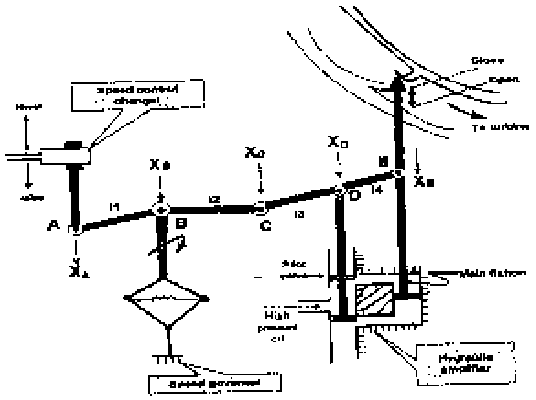


Fig. 3 Speed governing system

2.2 Governor Modle

The input to the hydraulic amplifiers is the position X_D at point D of the pilot valve. The output is the position X_E at the point E of the main piston . Because of the high pressure hydraulic pilot valve, the force amplification is very great. The position changes by the main piston is due to piston changes of linkage point B resulting from speed changes, or directly by moving the linkage point A by 'raise' or 'lower' command of the speed changer.

3-Design of Conventional Excitation and Governor Conrol

The main objective of the automatic voltage regulator (AVR) is to control the terminal voltage by adjusting the generator exciter voltage. The AVR must keep tracking the generator terminal voltage all the time and under any load condition. Linear optimal excitation and governor control is an application of modern optimal control theory in power system [11]. The block Diagram of Linear optimal Excitation and speed govern Control systems are shown in Fig.4 and Fig.5, respectively.

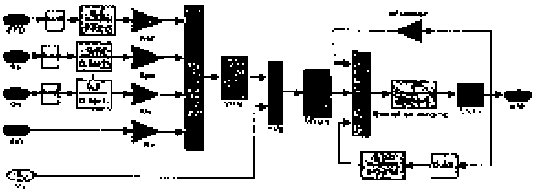


Fig. 4 Linear Optimal Excitation Control Block Diagram

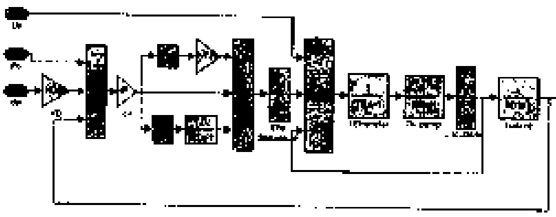


Fig. 5 Speed Govenor Control Block Diagram

where the inputs **Vs** and **Us** are a compensating signals that will be generated by *Neuro- Fuzzy* controller.

4- Neuro-Fuzzy System Design

In a hybrid Neuro-Fuzzy System (NFS), a neural network and a fuzzy system are combined into one homogeneous structure. Neuro-fuzzy system is intended to synthesize the advantages of both neural networks and fuzzy systems in a complementary way to overcome their disadvantages; neural network learning techniques facilitate fuzzy system tuning. There are several approaches for the integration of neural networks and fuzzy system. The kind of neuro-fuzzy systems of interest for this work have several common defining characteristics. The NFS approximates an n-dimensional, usually unknown, function that is partially defined by a set of input-output data. The NFS is a fuzzy system whose knowledge rules represent the relation among samples of the given data. The components of the NFS are determined using neural network learning algorithms applied to the given data. For the purpose of learning, the fuzzy system may be represented by a three-layer feed forward neural network. The first layer represents the input variables, the middle layer represents the fuzzy rules, the third layer represents the output variables, and the connection weights are given specified with fuzzy sets. The neuron units evaluate t-norms and t-conorms operators as activation function. Models with more than three layers and fuzzy sets as activation functions are also possible. In general, the neural network representation vividly illustrates the parallel nature of fuzzy systems [13].

Several methods are currently available to synthesize a neuro-fuzzy system: Generalized Approximate Reasoning based intelligent Control (GARIC), Neuro-Fuzzy Controller (NFCON), Dynamic Evolving Neuro-Fuzzy Inference System (DENFIS), Adaptive Neuro Fuzzy Inference System (ANFIS), etc. In this work, the neuro-fuzzy systems are synthesized using the general-purpose adaptive neuro fuzzy inference system (ANFIS) technique [13,14].

4.1 Adaptive Neuro-Fuzzy Inference System (ANFIS)

Sugeno Fuzzy ANFIS Model was proposed by Roger Jang in 1992 [13,14]. The architecture of a two input two rule ANFIS is shown as Fig. (6).

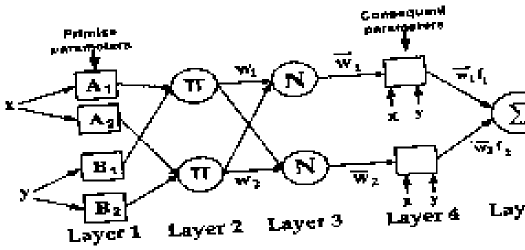


Fig. (6) ANFIS Architecture of a Two-Input-One-Output Sugeno Fuzzy Model with Two Rules

The ANFIS has five layers, where mode functions of the same layer have the same function as described below [14]. Functionally speaking, the ANFIS architecture is completely equivalent to a Sugeno fuzzy inference system. However, by implementing a fuzzy controller as ANFIS, we can easily employ the back-propagation-type learning procedure to find

its parameters for achieving a minimal error measure.

Assuming that the training data set has P entries and the output layer has only one node, the error measure for the pth entry of training data is:

$$E_p = \frac{1}{2}(\hat{y}_p - y_p^L)^2$$

where $\hat{y}_p$ is the pth component of desired vector and y_p^L is the pth component of actual output vector. For each training data, a forward pass is performed and then starting at the output layer, a backward pass is used to compute $\partial E_p/\partial y_p$ for all internal nodes.

For the output node:

$$\frac{\partial E_p}{\partial y_p^L} = -(\hat{y}_p - y_p^L)$$

While for the internal nodes in layer k;

$$\frac{\partial E_p}{\partial y_{ip}^k} = \sum_{n=1}^{k_1} \frac{\partial E_p}{\partial y_{np}^{k+1}} \frac{\partial y_{np}^{k+1}}{\partial y_{ip}^k} \qquad (6)$$

where $y^k_{i,p}$ is the output of the node in the ith position of kth layer which has k nodes and k_1 is the number of nodes in (k+1) th layer.

Assuming α is a parameter of the adaptive network:

$$\frac{\partial E_p}{\partial \alpha} = \sum_{y^* \in S} \frac{\partial E_p}{\partial y^*} \frac{\partial y^*}{\partial \alpha} \qquad (7)$$

where S is the set of nodes whose outputs depend on α. The goal is to minimize the overall error $E=\sum E_p$.

General learning rule:

$$\Delta\alpha = -\eta \frac{\partial E}{\partial \alpha} \qquad (8)$$

In which η is the learning rate and

$$\frac{\partial E}{\partial \alpha} = \sum_{p=1}^{P} \frac{\partial E_p}{\partial \alpha} \qquad (9)$$

Also, similar to the training of conventional neural network, a momentum term is added for a better convergence: (4)

$$\Delta\alpha(t) = -\eta \frac{\partial E}{\partial \alpha} + \beta\Delta\alpha(t-1) \qquad (10)$$

where β is the momentum factor and $\Delta\alpha(t-1)$ is the change of α in the last step.

Essentially, an adaptive network is a superset of a multi-layer feedforward neural network with supervised learning capability. An ANFIS network consists of nodes a directional links through which the nodes are connected. Each node performs a particular function (5) which may vary from node to node. The choice of each node function depends on the overall input-output function according to which the adaptive network is required to perform. Whereas in an

ANFIS, the adaptive parameters pertain to the links between the nodes, there the links only indicate the direction of flow of signals and part or the entire node contain the adaptive parameters[13]. These parameters are specified by the learning algorithm and should be updated to achieve a desired input-output mapping. Similar to the ANN with supervised learning algorithm, the learning rule of adaptive network is based on gradient descent.

4.2 ANFIS for Excitation and Governor Control

The Excitation and governing control of SMIB consists of two MISO fuzzy systems that provide the feedforwared control signals for the Excitation , U_{Eff}, Governing , U_{Gff} Control Signal in terms of the electrical power P_e , speed deviation, dw_d, and terminal voltage, V_d, set-point.

Both ANFIS systems for excitation and for governor control are of the same structure as shown in Fig.8. To this aim , the fuzzy system is represented as a 3-input- 1-output 5-layer feed forward neural network, as shown in Fig.8.For the case where, without lose of generality, each input signal spans its whole operating range with three overlapping fuzzy regions. That is using

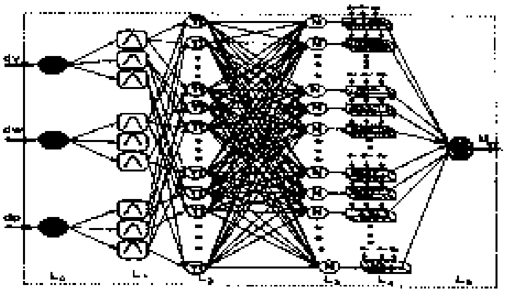


Fig.(7) ANFIS Structure With 3-Input –one-output

three fuzzy sets with Gaussian-Membership function and linguistic terms : low, medium, and high. Therefore, for this case a complete knowledge base will have 3x3 x3=27 rules of the given in Fig(7). Also the network will have 3 distribution units in layer L_0, 9 neurons in L_2, L_3, and L_4, and 1 neuron in L_5. With these dimensions, the number of parameters to determine is calculated as follows: 27 rules x 4 consequents per rule =108 consequent parameters, and 3 inputs x 3 membership functions per input x 3 parameters per membership function = 27 membership function parameters. Then, the total number of parameters to be determined is 108+27 =135 per fuzzy system. This numbers clearly illustrate the difficulty of tuning a fuzzy system following a trial & error approach, which simply gets worse as the number of input linguistic terms increases. Fortunately, this process can be fully automated using the neuro-fuzzy paradigm (ANFIS).

5- SIMULIK Circuit

The SIMULIK of SMIB plant with (ANFIS) controller of excitation and governing system by us MATLAB/SIMULINK with S_FUNCTION technique is shown in Fig.(9). The controllers block is implemented as two (MISO) of ANFIS with three input each is three membership function and two signal **Vs** and **Us** which compensation the linear excitation and governor speed control system shown in Fig.4and Fig.5 respectively. The generator and system parameters are given in Table-1

Table -1 Parameters of Model System

Xd	Xq	Xd'	Xq'	X2	Tdo
0.679	0.345	0.166	0.036	0.2	0.6
Tqo	H	D	Xt	Xl	Pn
0.6	0.1	0.01	0.2	1.6	0.1

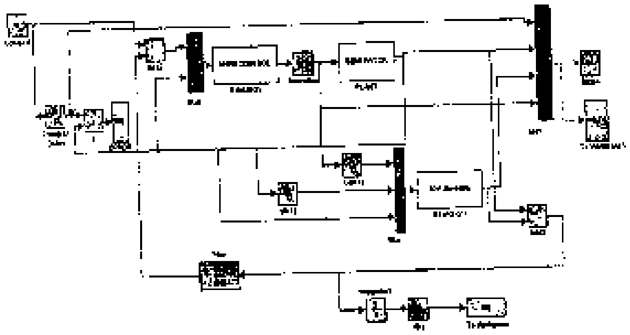


Fig. 8 Simulink SMIB with ANFIS Compensated Controller

6- Simulation Results

To been demonstrate the efficiency of the proposed ANFIS controller, several simulation tests have been performed, where the proposed controller was confronted to a number of small and large disturbances. In this section we demonstrate the effectiveness. The ANFIS controller by applying it to excitation governing control system of SMIB plant.

The test result are illustrated to compare that two controllers are used in this section through the following three test conditions:

1- A 3-phase short circuit clearing after 0.1s at the generator terminal (P_T=1 p.u and Q_T=0.2 p.u)

2- A step change in reference voltage -10% at the same power in step one.

3- An open circuit in transmission line over 0.2s at the same power in step one.

Comparing response curve of the conventional, Fuzzy-Neural control (CC and ANFIS , respectively) of excitation and governing system are shown from Fig.9 to Fig.17. In theses figures, generator terminal voltage, speed deviation, exciter input voltage responses are shown at different previous tests.

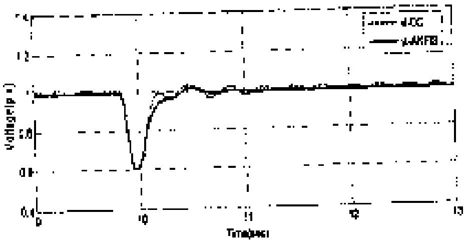


Fig. 9 Generator Terminal Voltage Response under 3-ph short circuit

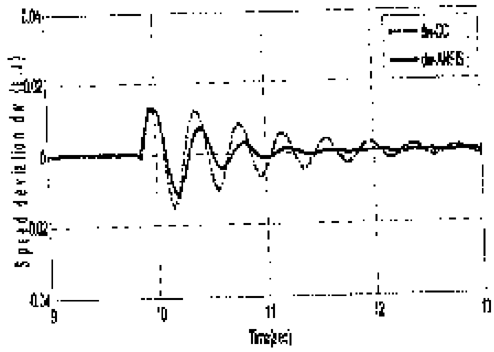


Fig.10 Generator Speed deviation Response under 3-ph short circuit

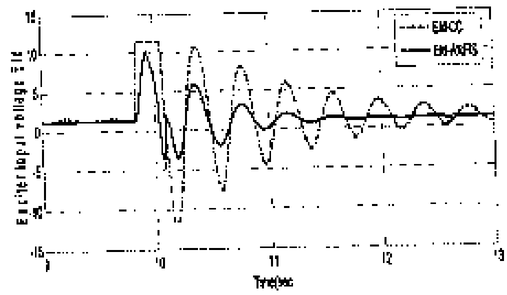


Fig.11 Generator Exciter Input Response under 3-ph short circuit

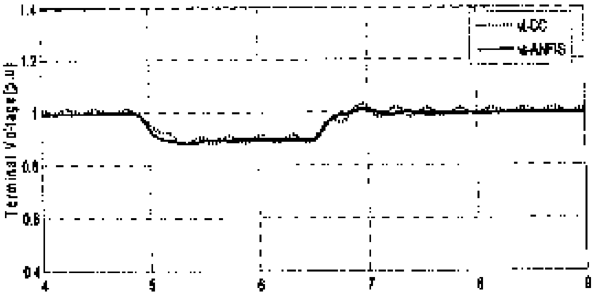


Fig.12 Generator Terminal Voltage Response under step change in Reference Voltage

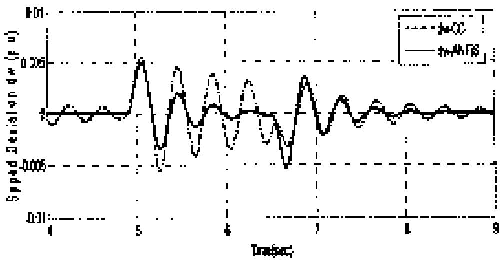


Fig.13 Generator Speed deviation Response under step change in Reference Voltage

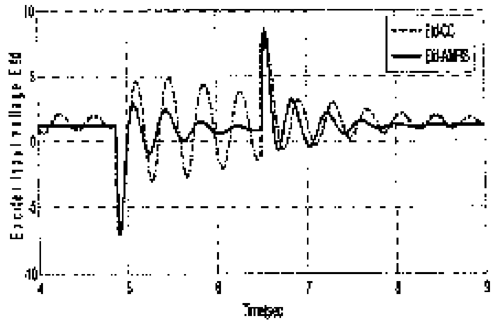


Fig.14 Generator Exciter input Response under step change in Reference Voltage

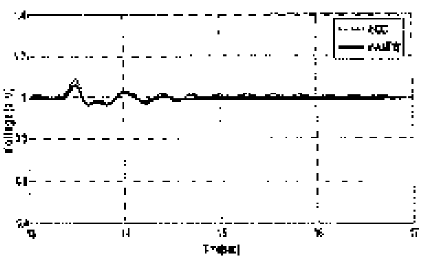


Fig.15 Generator Terminal Voltage Response under Open Transmission Line

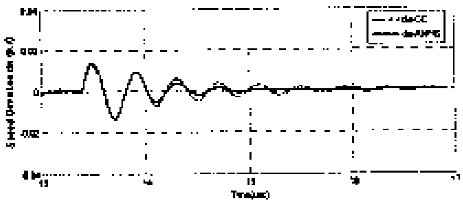


Fig.16 Generator Speed deviation Response under Open Transmission Line

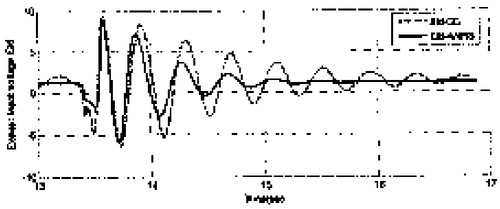


Fig.17 Generator Exciter input Response under Open Transmission Line

7-Conclusions

A design of the flexible , adaptive , multivariable output feedback , neuro-fuzzy coordinating stabilizing control of the exciter ad governor loops of single–machine-infinite bus has been proposed in this paper. The main feature of the proposed control is that it does not require a reference model or inverse system model and avoids the use of probing signals.

A generalized controller design mythology, called self-learning neuro-fuzzy controller has been used minimize the difference between an actual trajectory and given desired trajectory. This methodology employs the adaptive network as a building block and the back-propagation gradient method.

Comparing response curves of the conventional with those of ANFIS controller, it could be concluded that the system performance is highly improved.

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