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Full Length Research Paper

An efficient neuro-fuzzy control of synchronous generator: A case study

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Synchronous machine is an AC rotating machine whose speed under steady state condition is proportional to the frequency of the current in its armature. This paper presents an efficient neuro-fuzzy control of synchronous generator. It has been compared with fuzzy control and multilayer control. As evinced through the simulation results, neuro-fuzzy and type-2 are comparatively superior over the architectures.

Key words: Control, neuro-fuzzy, synchronous generator.

INTRODUCTION

Synchronous generator runs at a constant speed and draws its excitation from a power source external or independent of the load or transmission network it is supplying. Synchronous machine is an AC rotating machine whose speed under steady state condition is proportional to the frequency of the current in its armature (Rahman and Hiti, 2003; Batzel and Lee, 2003). The magnetic field created by the armature currents rotates at the same speed as that created by the field current on the rotor, which is rotating at the synchronous speed and a steady torque results. Since the reactive power generated by a synchronous machine can be adjusted by controlling the magnitude of the rotor field known as synchronous condensers, may be more economical in the large sizes than static capacitors (Guo et al., 2003; Uddin et al., 2004).

Neuro-fuzzy modeling allows a fuzzy system to be refined by neural training, thus avoid lengthy trial-and-error phases in defining both membership functions and inference rules. An approach to obtain simple neuro-fuzzy models is proposed, which reduces the number of rules by means of a systematic procedure that consists in successively removing a rule and updating the remaining rules in such a way that the overall input-output behavior is kept approximately unchanged over the entire training set. A formulation of the proper update is described and a criterion for choosing the rules to be removed is also provided. Initial experimental results show the effectiveness of the proposed method in reducing the complexity of a neuro-fuzzy system by using its input-output data (Chiricozzi et al., 1996; Parasiliti et al., 1996; Lightbody and Irwin, 1997; Amin, 1997; Cabrera et al., 1997).

This paper presents an efficient neuro-fuzzy control of synchronous generator. It has been compared with fuzzy control and multilayer control of synchronous generator. As evinced through the simulation results, neuro-fuzzy and type-2 are comparatively superior over the architectures.

METHODOLOGY

The mathematical model of synchronous generator has been discussed in the following sub sections. This mathematical model helps in taking various control decisions keeping the stability in to consideration. Reference frame theory is quite important for the analysis of different electric machines analysis. The model of two pole salient pole synchronous superconducting machine with damper windings is shown in Figure 1 and 2 d-axis is aligned with the N-pole of the rotor and q- axis is 90 degree apart from d-axis.

Mathematical model comprises of the following basic equations:

$$v_{ds} = R_s i_{ds} + \frac{d\phi_{ds}}{dt} - \omega\phi_{ds} \tag{1}$$

$$v_{qs} = R_s i_{qs} + \frac{d\phi_{qs}}{dt} + \omega\phi_{ds} \tag{2}$$

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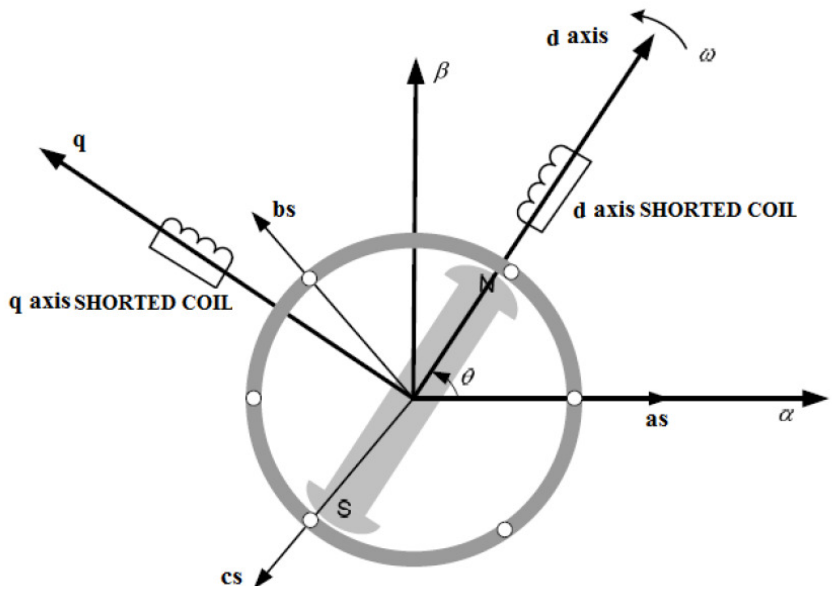

Figure 1. D-q model of synchronous generator.

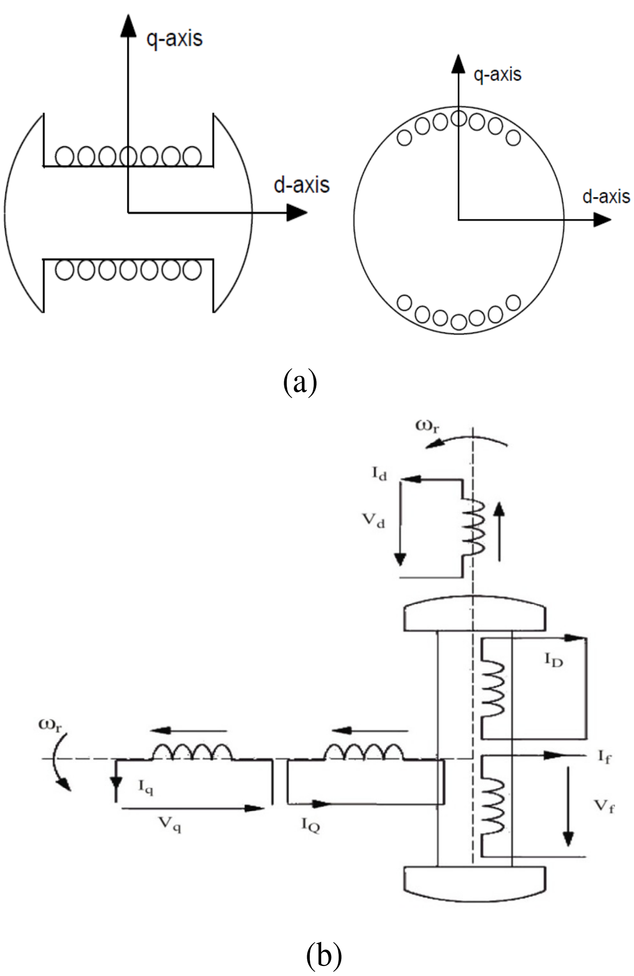

Figure 2. (a) d-q axis representation in case of synchronous generator. (b) d-q model of synchronous generator.

$$v_f = R_f i_f + \frac{d\phi_f}{dt} \tag{3}$$

$$J\frac{d\Omega}{dt} = C_e - C_r - B\Omega \tag{4}$$

$$\phi_{ds} = L_{ds} i_{ds} + M_{fd} i_f \tag{5}$$

Here, v_{ds}, R_s i_{ds}, Φ_{ds}, ω_{ds}, v_{qs} i_{qs}, Φ_{ds}, v_f R_f, i_f, J, B, Ω, L_{ds}, M_{fd} are direct axis stator voltage, stator resistance, direct axis stator speed, quadrature axis stator voltage, field voltage, direct axis stator flux, field voltage, field resistance, current density, magnetic flux density, direct axis inductance and mutual inductance, respectively. Figure 3 shows schematic diagram with fuzzy control (Rahman et al., 1998; Dumitrescu et al., 1999; Jongman et al., 2009; Andersen and Dorrell, 2010).

Problem formulation

Fuzzy model reference learning controller (FMRLC) in synchronous generator terminal voltage and reactive power control is designed so that its learning controller has the ability to improve the performance of the closed-loop. The FMRLC controller is superior to conventional self tuning controllers which continue to tune the controller parameters because it will tune and to some extent remember the values that it had tuned in the past.

Figure 4 shows the functional block diagram of the FMRLC. It is made up of four main parts; the plant, the fuzzy controller to be tuned, the reference model, and the learning mechanism (an adaptation mechanism). The FMRLC uses discrete time signals r(KT) and y(KT) with T as the sampling period. It also uses the learning mechanism to observe numerical data from a fuzzy control system (Ching-Hung and Ching-Cheng, 2000; Wai, 2001).

The considered fuzzy rules are as below. A similar fuzzy rule based on the developed system mathematical model has been

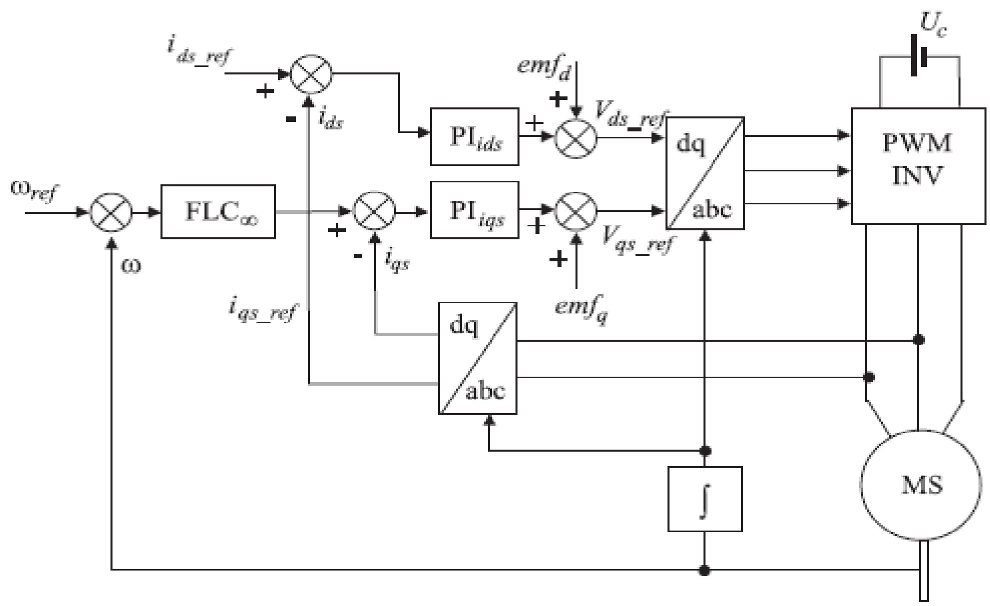

Figure 3. Schematic diagram of synchronous generator control.

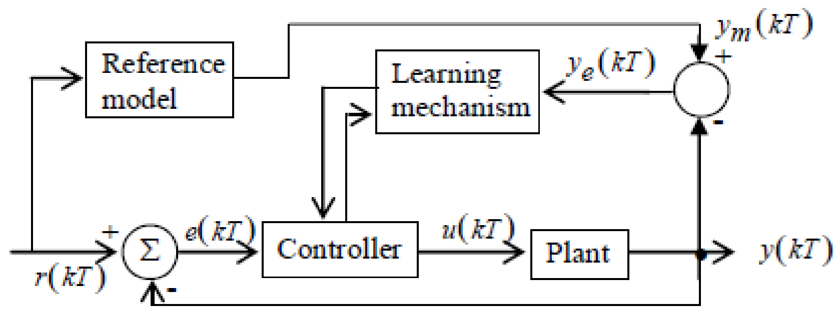

Figure 4. Fuzzy-neuro controller for synchronous generator.

implemented in FIS and ANFIS.

IF torque error is SMALL AND error derivative is VERY SMALL THEN stator current compensation is SMALL.

The fuzzy control system loop operates to make y(KT) track r(KT) by manipulating u(kT), while the adaptation control loop seeks to make the output of the plant y(kT) track the output of the reference model ym(kT) by manipulating the fuzzy controller parameters. The synchronous generator which represents the plant has an input u (kT) from the fuzzy controller and terminal voltage output y(kT). The input to the fuzzy controller is the error. It is given in Equations 6 and 7.

$$e(kT) = r(kT) - y(kT) \qquad (6)$$

$$c(kT) = \frac{e(kT) - e(kT - T)}{T} \qquad (7)$$

In Figure 5, the schematic of neuro-fuzzy has been shown which involves the graphical representation of the processing of knowledge in the neuro-fuzzy based model. This model is able to learn and optimize the control requirement. In Figure 6, the general architecture of ANFIS represents how the different layers are performing according to the weights assigned to them as in layers 1, 2, 3, 4 and 5. Figures 6 and 7 show the architecture and schematic of synchronous generator and ANFIS in MATLAB (Rahman and Hoque, 1998; Ching-Hung and Ching-Cheng, 2000; Karakaya and Karakas, 2008; Sumina and Bulic, 2008).

Simulation and testing

The neuro-fuzzy control simulink diagram is shown in Figure 7. It considers the supply, the machine, limiter circuits, breaker etc.

The simulink diagram as shown in Figure 8 depicts the fuzzy logic control of synchronous generator. It shows the machine, decoder, test signals etc.

The knowledge-base modifier performs the function of modifying the fuzzy controller's rule-base to affect the needed changes in the process inputs and it is depicted in Figure 9.

Figure 9 exhibits performance improvement of rotor speed, mechanical torque, electrical power and electrical power simultaneously on CRO. Table 1 show all the possible rules which

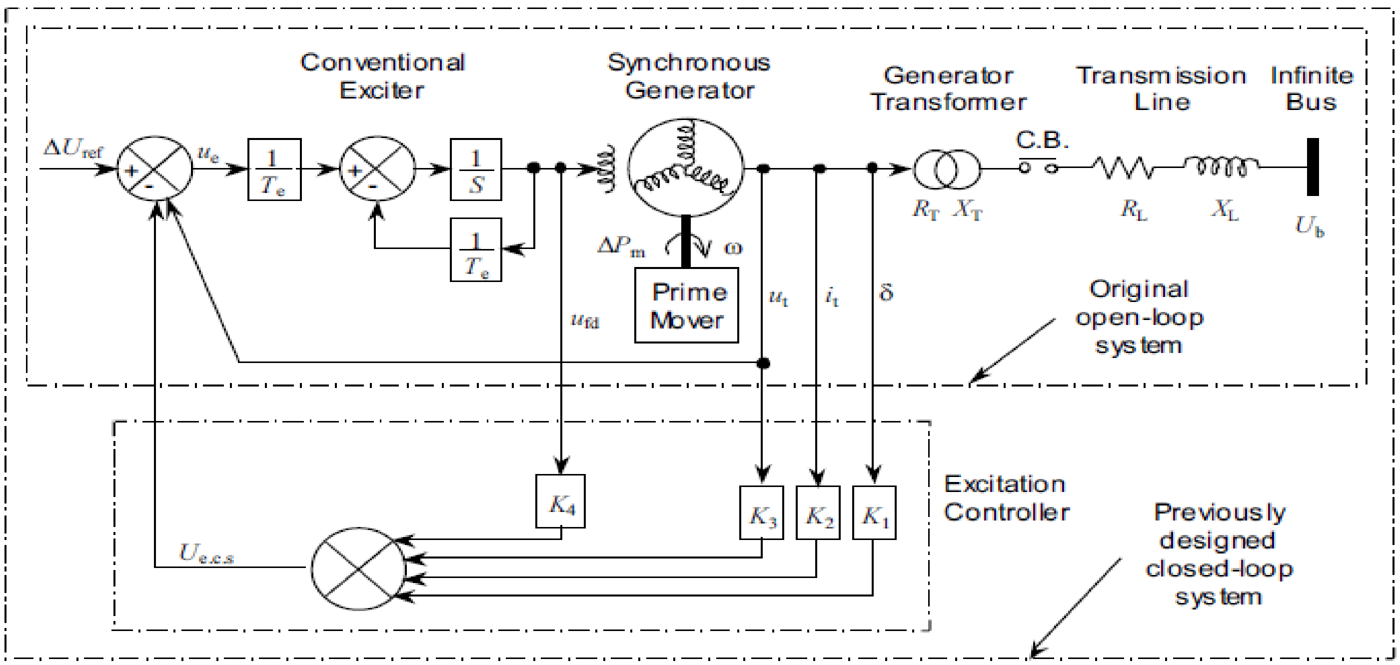

Figure 5. Detailed schematic diagram for adaptive controller for synchronous generator.

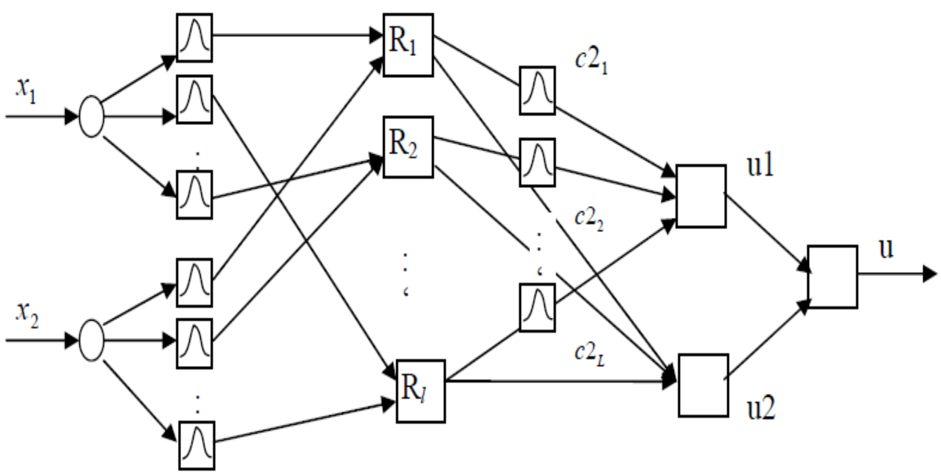

Figure 6. Neuro-fuzzy architecture.

can be made in fuzzy rule base for above fuzzy based synchronous generator control system and the knowledge based modifier which optimizes the performance. Rules have being formulated for error and change in error.

RESULTS AND DISCUSSION

Now the techniques of neuro fuzzy will be applied to test for better control strategy. Figure 10 depicts the ANFIS graph for error and epochs for the synchronous generator. Figure 11 shows the ANFIS neural network architecture.

The fuzzy neuro architecture implemented in the system has been shown in Figure 11 and the simulink representation of neuro fuzzy control is shown in Figure 12.

Figure 12 shows the response curves for stator current, rotor speed and torque in fuzzy neuro based control strategy. The considered system is stabilized after t = 0.13. It is evident that the current and speed get saturated after certain settling time. The overshoot is also reduced significantly and eventually zero offset is being

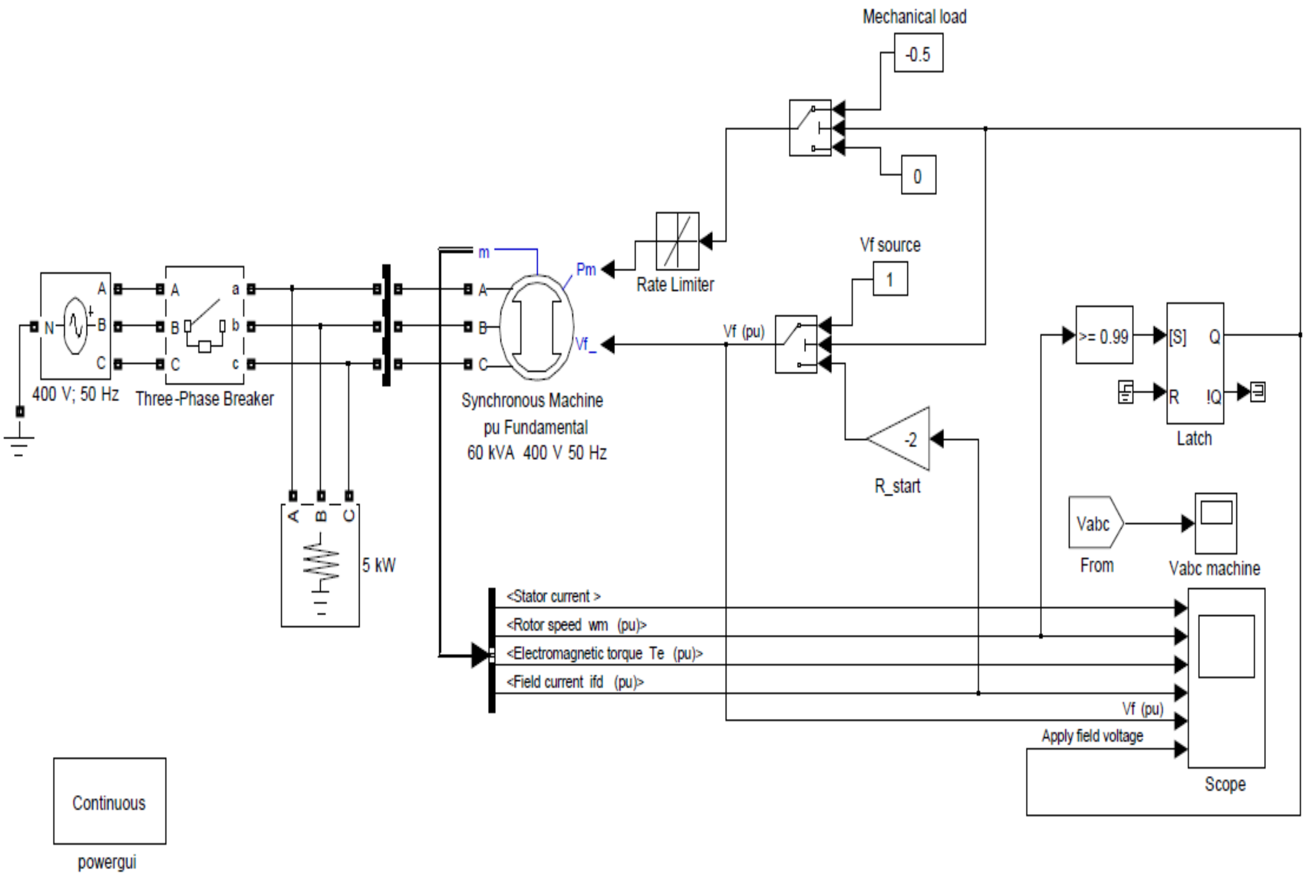

Figure 7. Neuro-fuzzy control of synchronous generator.

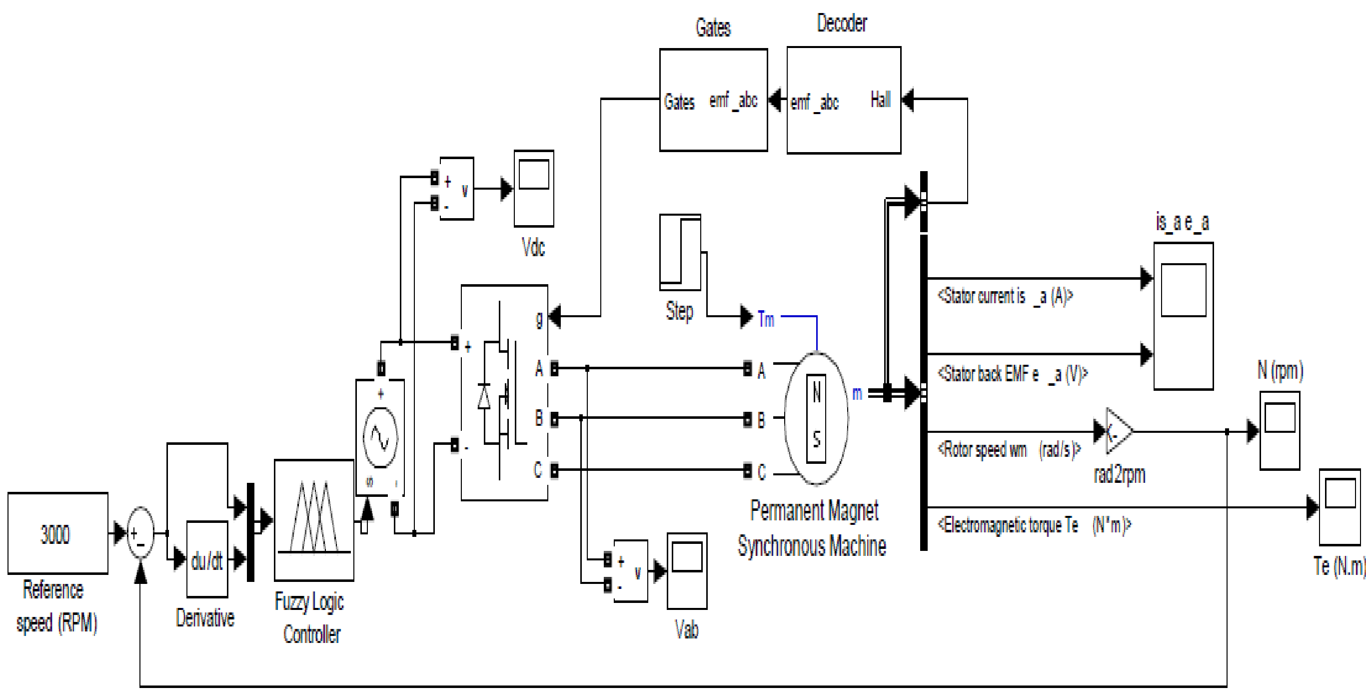

Figure 8. Fuzzy logic control of synchronous generator.

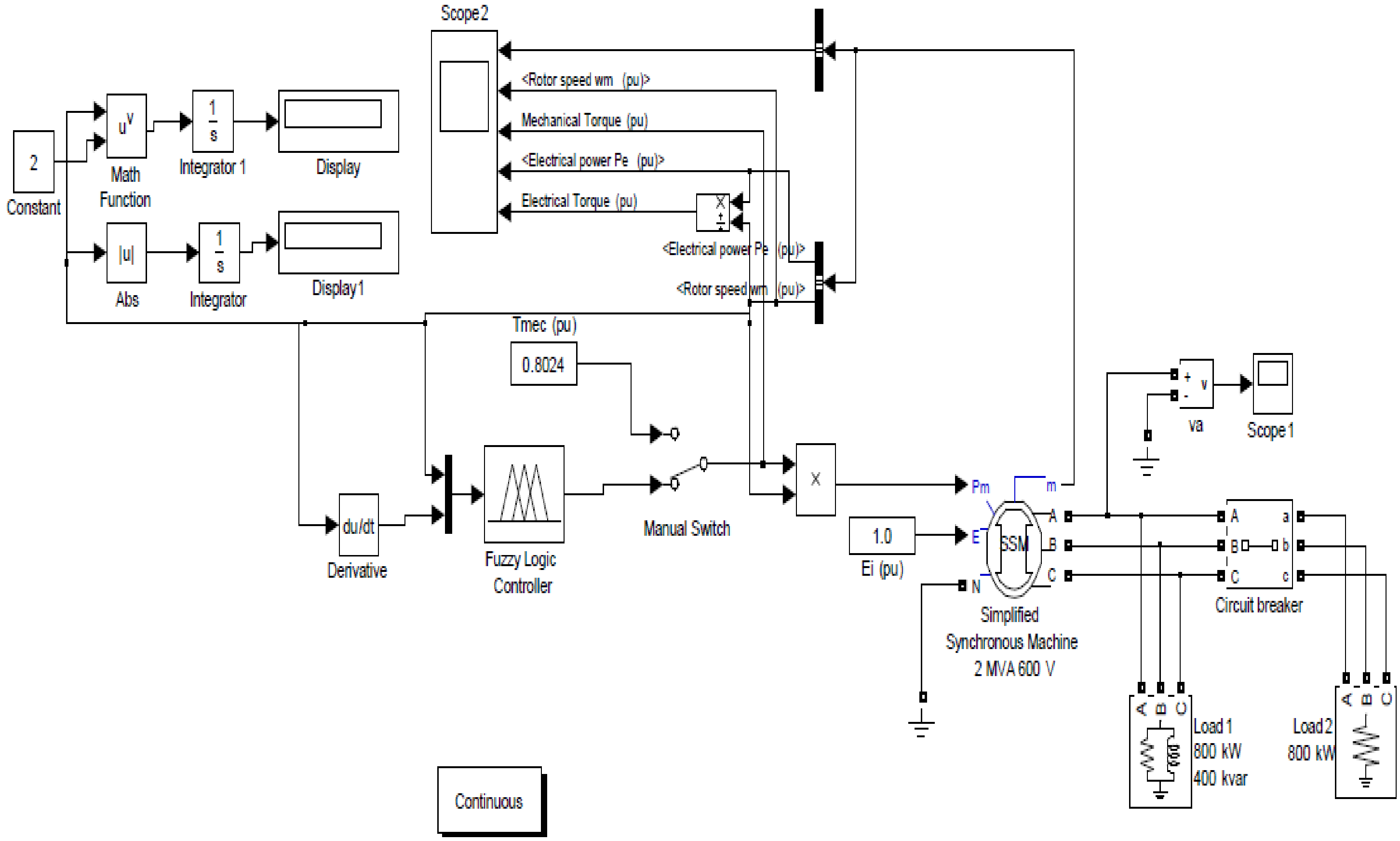

Figure 9. Knowledge-base modifier for synchronous generator.

Table 1. Fuzzy rule base for inputs and output.

u(t)		e(t)						
		NB	**NM**	**NS**	**ZO**	**PS**	**PM**	**PB**
	NB	NB	NB	NB	NB	NM	NS	ZO
	NM	NB	NB	NB	NM	NS	ZO	PS
	NS	NB	NB	NM	NS	ZO	PS	PM
Δe(t)	ZO	NB	NM	NS	ZO	PS	PM	PB
	PS	NM	NS	ZO	PS	PM	PB	PB
	PM	NS	ZO	PS	PM	PB	PB	PB
	PB	ZO	PS	PM	PB	PB	PB	PB

achieved in neuro fuzzy control. However, there is some small and finite offset with fuzzy control. The accuracy is being ascertained by finding IAE and ITAE error criteria, as applied in both the cases.

Conclusions

From the above case studies we have calculated IAE that is, integral absolute error and ITAE that is, integral time absolute error parameters for each of the type of control architecture. The calculation for IAE and ITAE in Table 2 gives a comparative analysis for considered control techniques. These performances indices of IAE and ITAE help in decision taking regarding selection of control architecture.

Figure 13 presents the step response of synchronous generator it has peak amplitude of 0.331, overshoot percentage of 65.3%,rise time of system is 0.519 s and settling time is 12.9 s. System took 1.4sec to settle down

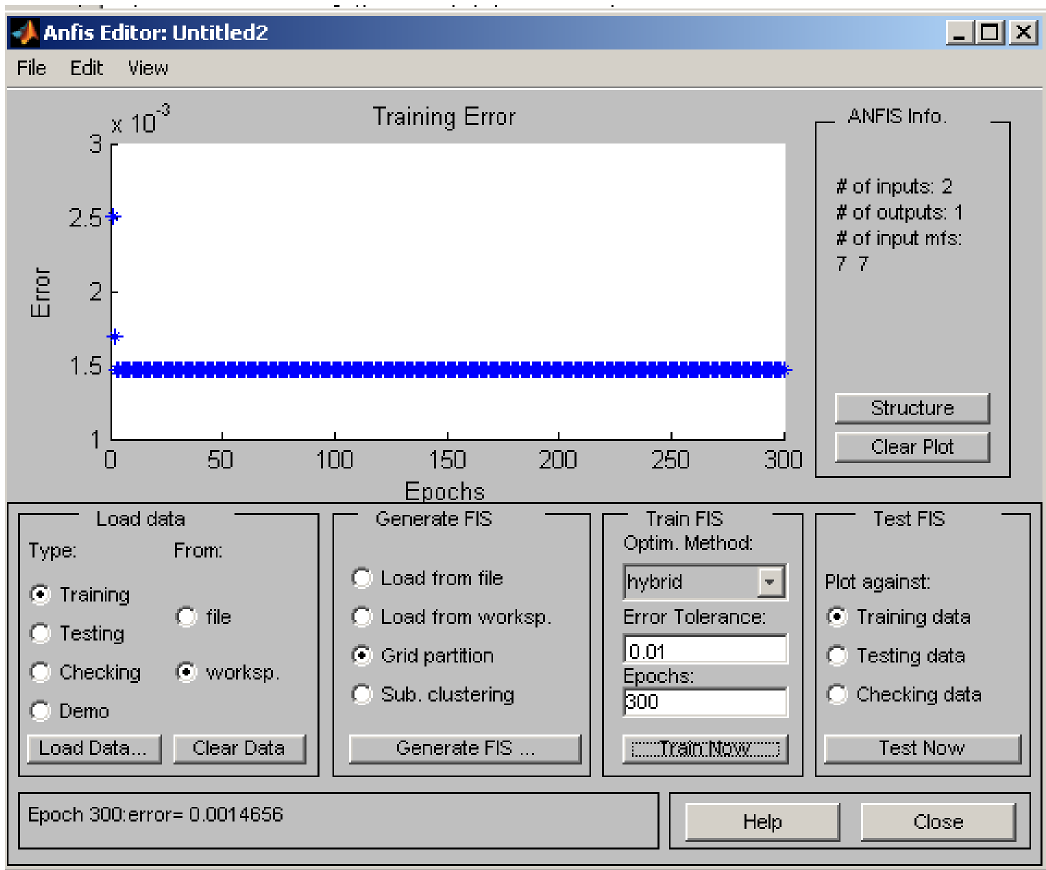

Figure 10. Graph between error and epoch of neural network.

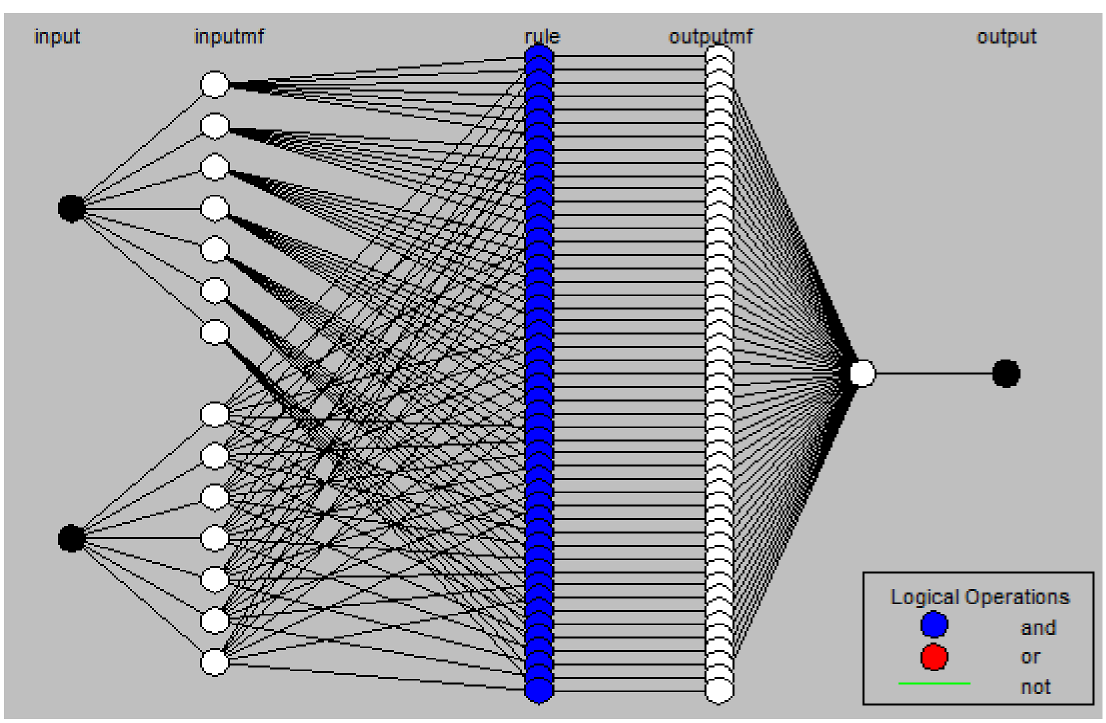

Figure 11. ANFIS neural network architecture.

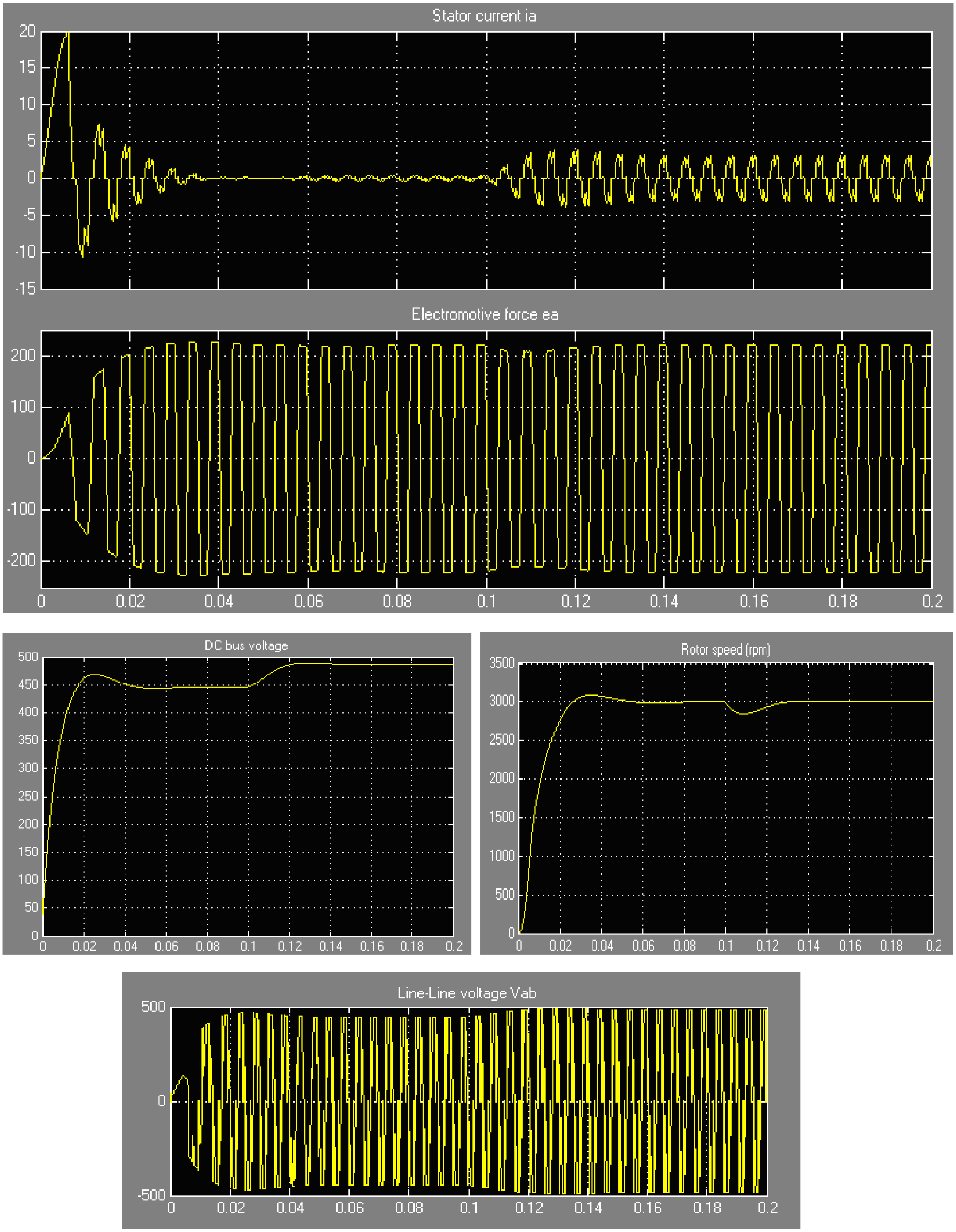

Figure 12. Response curves of stator current, rotor speed, and torque in fuzzy neuro control of synchronous generator.

Table 2. IAE and ITAE calculations.

S/n	Parameter	Type-1	Type-2	Neuro fuzzy	Multi layer
1	IAE	4.755	4.428	7.243	8.56
2	IATE	0.3665	0.312	0.6035	0.77

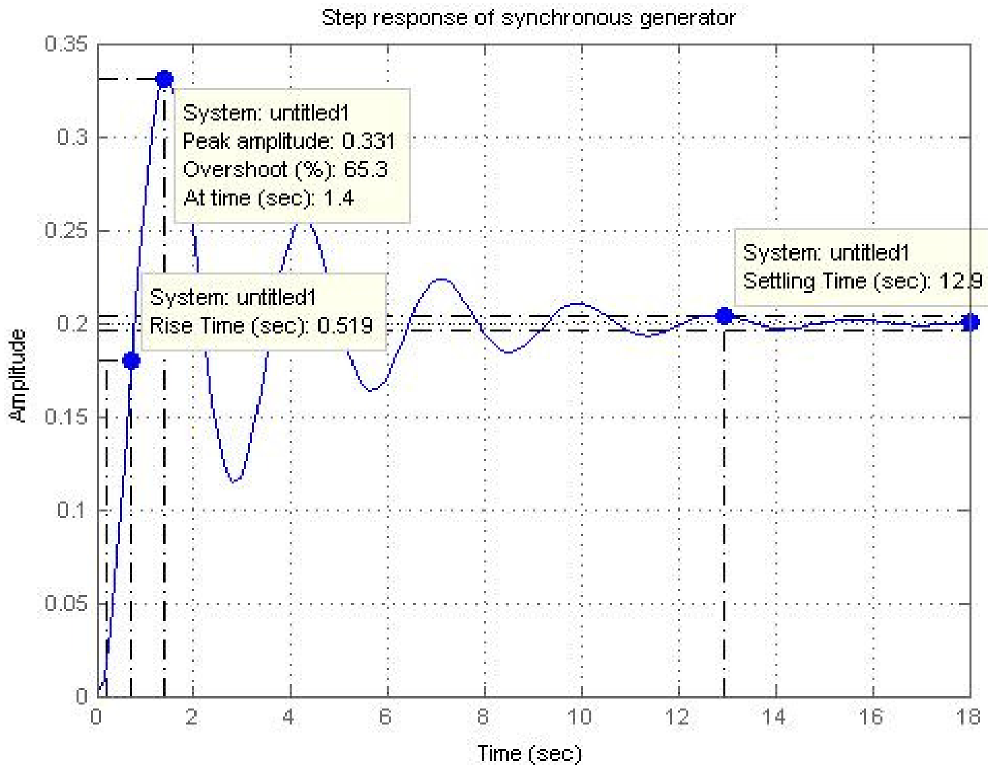

Figure 13. Time response of synchronous generator at step increase in torque.

and to provide stable performance.

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