ADAPTIVE FUZZY LOGIC CONTROL FOR A TURBO-GENERATOR

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ABSTRACT

Adaptive fuzzy logic controllers (AFLC) provide attractive solution to problems encountered due to nonlinear effects. They also allow for design in cases where models are incomplete, unlike most design techniques. The major advantage of the (AFLC) is that they provide a common framework for incorporating both numerical and expert linguistic information. This paper, presents two different methods of the adaptive fuzzy logic controllers (AFLC). The first method is based on changing the scaling factors and the other method is based on changing the membership functions shape. These two algorithms are applied to simulate A.C. single- input single-output turbo-generator system connected to an infinite bus-bar, to demonstrate the effectiveness and robustness of these design approaches.

Keywords: Fuzzy logic controller, adaptive fuzzy logic controller, power systems.

INTRODUCTION

In the last two decades, fuzzy logic control has become one of the most important fields in artificial intelligence and process control application. A fuzzy logic controller is a rule based controller which uses information in the manner as human experts. It does not require the complex mathematics associated with classical control techniques.

The fuzzy logic controller was introduced by Zadeh [1], around twenty seven years ago. It is nonlinear in nature and so they can be designed to cope with a certain amount of process non-linearity. However, such design is difficult, especially if the controller must cope with non-linearity over a significant portion of the operating range of the process. Also, the rules of fuzzy logic controller do not in general, contain a temporal component, so they cannot cope with process changes over time. So there is a need for adaptive fuzzy logic controller as well. Fuzzy logic controller contains a number of sets of parameters that can be altered to modify the performance of the controller. These are:

- *The scaling factors for each variables,*
- *The fuzzy set representing the meaning of linguistic values,*
- *The fuzzy control rules (if-then rules).*

If any of these parameters is altered we will call the controller an adaptive fuzzy logic controller. Each of these sets of parameters has been used as the controller parameters to be adapted in different adaptive fuzzy logic controller.

The aim of this paper is to present two different designs of the adaptive fuzzy logic controller using the change in the scaling factors and altering the fuzzy set representing the meaning of linguistic values, for a nonlinear turbo-generator excitation system which is difficult to control by conventional methods.

ADAPTIVE FUZZY LOGIC CONTROLLER

The adaptive fuzzy logic controller consists of three parts, as shown in Figure 1: static fuzzy logic controller; performance monitor and adaptation mechanisms.

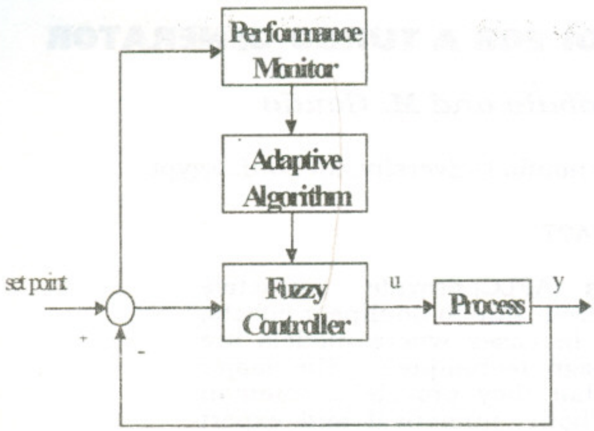


Figure 1 Performance adaptive FLC

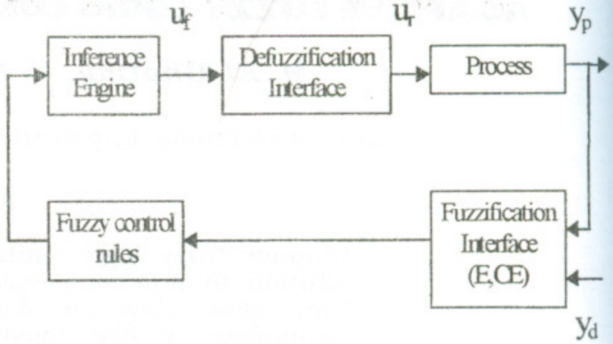


Figure 2 Structure of static FLC

Static Fuzzy Logic Controllers (SFLC)

Since the fuzzy control theory is somewhat new to the power community, it is appropriate to review here some basic concepts of fuzzy logic control. The reader interested in a more comprehensive review of the subject will find References 1,4 and 5, very helpful. In this section, we present the basic structure of the static fuzzy controller which is shown in Figure 2. The static fuzzy controller consists of four main functional blocks:

- *Fuzzification interface,*
- *Fuzzy control rules,*
- *Inference engine, and*
- *Defuzzification interface.*

Fuzzification Interface

The fuzzification interface consists of the following operation [4] :-

1. Compute the input variables (crisp values of error and change of error),
2. Perform a scale mapping that transfers the input variable ranges into a corresponding universe of discourse (Quantization/ Normalization),
3. Perform the fuzzification strategy that converts input crisp data into suitable linguistic variables, which may be viewed as labels of fuzzy sets.

The fuzzification strategy converts the crisp input data into fuzzy sets (linguistic variables) such as:

PVB:Positive very big	NVS:Negative very small
PB:Positive big	NS:Negative small
PM:Positive medium	NM:Negative medium
PS:Positive small	NB:Negative big
PVS:Positive very small	NVB:Negative very big
ZE: Zero	

The fuzzification action consists of a set of analog membership functions, describing the input linguistic terms. The membership function can be triangle-shaped, trapezoid-shaped, etc.

Fuzzy Control Rules

The dynamic behavior of a fuzzy system is characterized by a set of imprecise conditional statements which form a set of decision rules. The process can be expressed linguistically as a set of linguistic decision rules of the form :

IF (conditions are satisfied) THEN (action can be inferred)

There are four ways to derive fuzzy control rules [6,7]

1. They may be derived by referring to human operator's experience and/or control engineer's knowledge,

2. They may be derived by 9modeling the human operator's control actions,
3. They may be derived from a fuzzy model of the process,
4. The rules may be learnt by the controller (self-organization).

Inference Engine

The inference mechanism involves the following two functions:

1. Determine for any fuzzy controller input (error and change of error) which rules are applicable,
2. Determine the fuzzy control action by using fuzzy reasoning.

There are in general four methods of fuzzy reasoning [5], but the following method is the one used in this paper.

Fuzzy Reasoning of Mamdani's Minimum Operation Type

To explain the idea of this method, we will show the following example. For simplicity, assume that we have the following two fuzzy rules:

R1: IF e is A1 and ce is B1 THEN u is c1

R2: IF e is A2 and ce is B2 THEN u is c2

Let e_0 and ce_0 be the crisp values of the inputs e and ce (error and change of error). The truth values W_1 and W_2 of the premises are calculated by :

$$W_i = \mu_{Ai}(e_o) \wedge \mu_{Bi}(ce_o)$$

$$W_i = \min[\mu_{Ai}(e_o), \mu_{Bi}(ce_0)] \quad \text{where, i=1,2}$$

The membership function for each rule is calculated by:-

$$\mu_{Ri} = \min(W_i, \mu_{ci})$$

Which implies that the membership function $\mu_c(u)$ of the inferred consequence is given by:-

$$\mu_c(u) = \mu_{R1} \vee \mu_{R2}$$

$$= \max[\mu_{R1}, \mu_{R2}]$$

$$= \max[\min(W_1, \mu_{c1}), \min(W_2, \mu_{c2})]$$

This fuzzy reasoning method is illustrated in Figure 3, where the membership function is triangle shaped.

Defuzzification Strategies

The output of inference engine is a fuzzy set. As a process usually requires a non fuzzy control action (crisp value), a defuzzification strategy is needed. However, the main methods to tackle this problem are [8]:

1. The maximum criterion method
2. Mean of maximum method (MOM)
3. Center of gravity method (COG) :

This method takes the average of the control action values weighted by the grade of membership. In the case of discrete universe of discourse, the output U_0 is inferred by:

$$U_o = \frac{\sum_{i=1}^{n} \mu(u_i).u_i}{\sum_{i=1}^{n} \mu(u_i)}$$

where:

$\mu(u_i)$: Grade of membership function at u_i

n: The number of discrete points of fuzzy control action.

Performance Monitor

The alternative type of process monitor forms an assessment of controller performance based on readily measured variables. For the regulatory control problem, where the aim is to keep a process state variable at its specified set-point, a number of performance-related variables are of potential use. These include [9]: rise time, settling time, integral of the square error, integral of the absolute value of the error and overshoot.

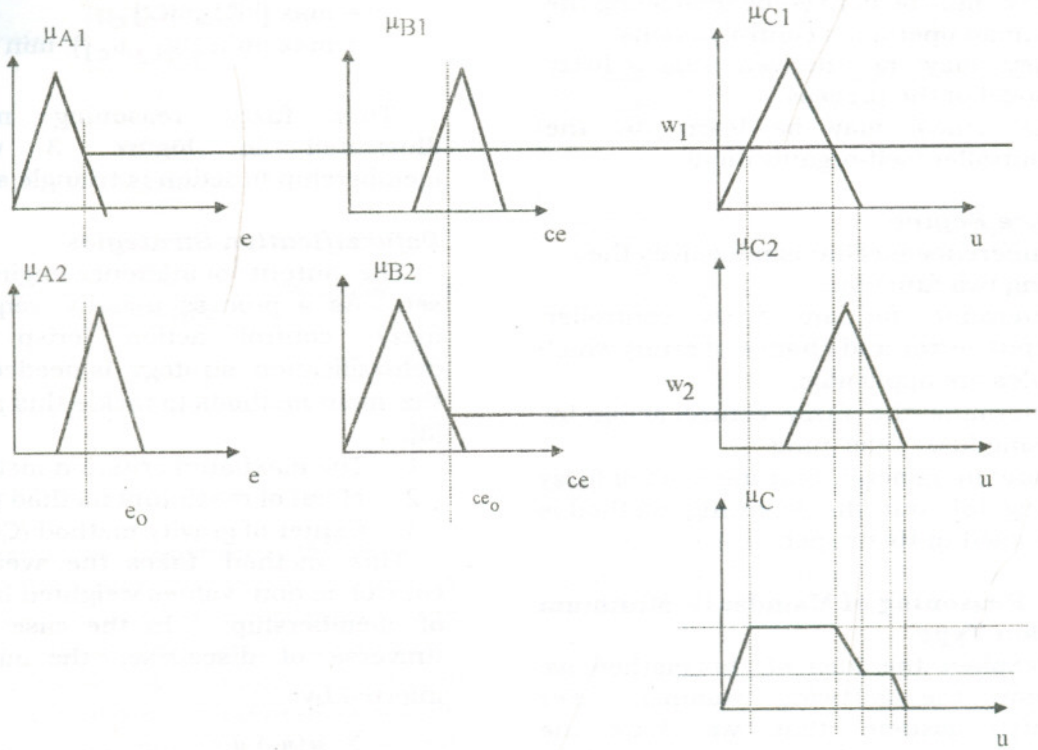


Figure 3 Fuzzy reasoning (Mamdani's minimum operation)

The choice of one or more performance measures depends on the type of response the control system the designer wishes to achieve. The final output of performance monitor, as seen by the adaptation mechanism, is either the actual values of performance measures [10], or a performance index derived from the performance measures [11,12].

Adaptation Mechanism

The adaptation mechanism must modify the controller parameters to improve the controller performance on the basis of the output from the process monitor. Adaptation mechanisms for fuzzy logic controller can be classified according to which parameters are adjusted. Parameters that can be adjusted include the scaling factors with which controller input and output values are mapped onto the universe of discourse of the fuzzy set definitions. The change in the scaling factors changes the sensitivity of the controller to the input, and so changes the controller gain. In this way, altering scaling factors is similar to gain tuning in standard PID controllers. The other tuning mechanizm is to alter the shapes of fuzzy set. An example where the sets are altered to increase the sensitivity of the controller to small values of the input is shown in Figure 4.

ADAPTIVE FLC FOR A NONLINEAR SINGLE-INPUT SINGLE-OUTPUT TURBO-GENERATOR

This section is concerned with the application of the (AFLC) for a turbo-generator exciter.

Excitation controllers are designed assuming constant mechanical torque input for the purpose of regulating the terminal voltage and improving the generators stability limit. The adaptive fuzzy control algorithms has been developed after some experiments in order to verify the fuzzy control rules, membership functions, scaling factors and the defuzzification strategy.

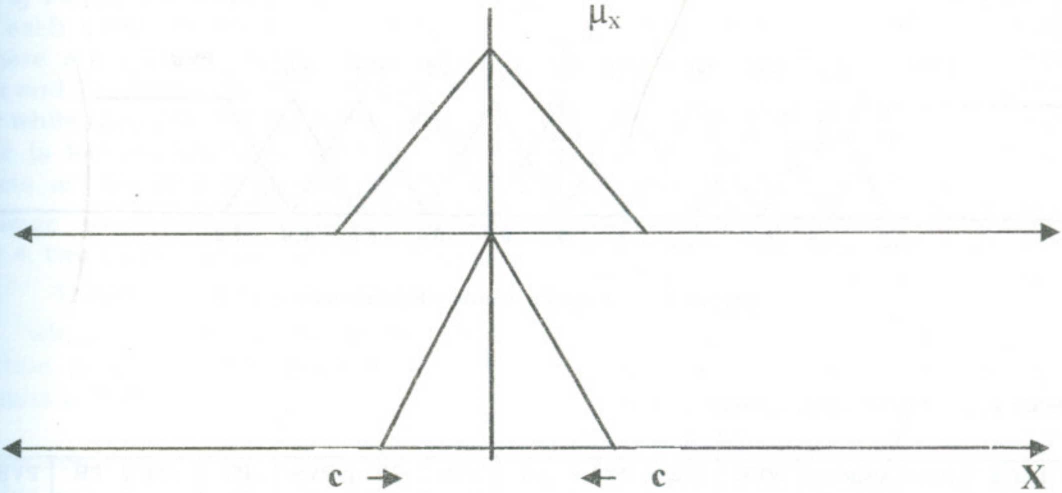


Figure 4 Example of the algorithm

Quantization / Normalization

The detailed structure of the fuzzy controller contains the scaling factors of the error and change of error, Ge, Gce. So the input variables are quantized using different scaling factors of error and change of error:

EN=Ge*e
CEN=Gce*ce

and a similar relationship holds for the control action which results from defuzzification strategy

U_o:-
U_p=Gu* U_o

Fuzzification Strategy

In this application, a fuzzy set then defined by assigning its membership function (we have 11 fuzzy sets, PVB, PB, PM, PS, PVS, ZE, NVS, NS, NM, NB, NVB). The membership function of the fuzzy sets used for fuzzifying the error, change of error and control action is similar and a triangle shaped function shown in Figure 5. For example,

NVB .... f_1= -5x-4
NB .... f_2= 5x+5
.... f_3= -5x-3
.... etc,

where f_i ; i=1,.....20 are the different segments assigned for each range of normalized universe of discourse .

In this application we use the same membership function for error, error change and control action. The difference between them is corresponding scaling factors. Table 1 represents the fuzzification strategy.

Fuzzy Control Rules

In this application we derive the fuzzy control rules by referring to the operator's experience and the control engineer's knowledge. Table 2 represents the applied fuzzy control rules (121 rules in all).

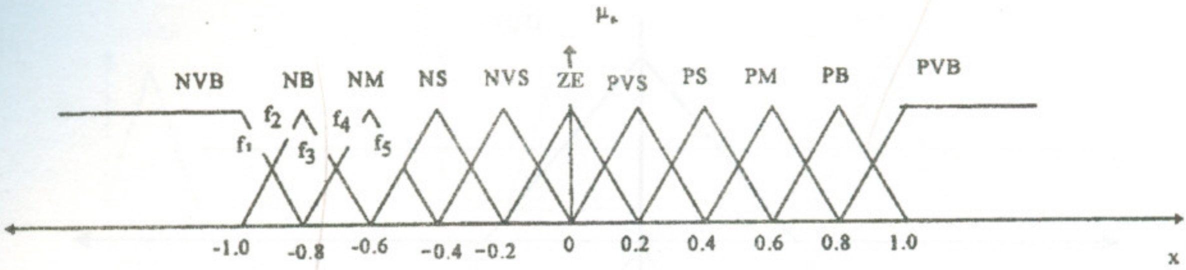


Figure 5 Triangle membership function

Table 1 Fuzzification strategy

Level number	Normalization variable, x	NVB	NB	NM	NS	NVS	ZE	PVS	PS	PM	PB	PVB
1	[-1 -0.8]	f_1	f_2	0	0	0	0	0	0	0	0	0
2	[-0.8 -0.6]	0	f_3	f_4	0	0	0	0	0	0	0	0
3	[-0.6 -0.4]	0	0	f_5	f_6	0	0	0	0	0	0	0
4	[-0.4 -0.2]	0	0	0	f_7	f_8	0	0	0	0	0	0
5	[-0.2 0]	0	0	0	0	f_9	f_{10}	0	0	0	0	0
6	[0 0.2]	0	0	0	0	0	f_{11}	f_{12}	0	0	0	0
7	[0.2 0.4]	0	0	0	0	0	0	f_{13}	f_{14}	0	0	0
8	[0.4 0.6]	0	0	0	0	0	0	0	f_{15}	f_{16}	0	0
9	[0.6 0.8]	0	0	0	0	0	0	0	0	f_{17}	f_{18}	0
10	[0.8 1]	0	0	0	0	0	0	0	0	0	f_{19}	f_{20}

Table 2 Applied fuzzy control rules

E \ CE	NVB	NB	NM	NS	NVS	ZE	PVS	PS	PM	PB	PVB
NVB	NVB	NVB	NVB	NVB	NVB	NVB	NB	NM	NS	NVS	ZE
NB	NVB	NVB	NVB	NVB	NVB	NB	NM	NS	NVS	ZE	PVS
NM	NVB	NVB	NVB	NVB	NB	NM	NS	NVS	ZE	PVS	PS
NS	NVB	NVB	NVB	NB	NM	NS	NVS	ZE	PVS	PS	PM
NVS	NVB	NVB	NB	NM	NS	NVS	ZE	PVS	PS	PM	PB
ZE	NVB	NB	NM	NS	NVS	ZE	PVS	PS	PM	PB	PVB
PVS	NB	NM	NS	NVS	ZE	PVS	PS	PM	PB	PVB	PVB
PS	NM	NS	NVS	ZE	PVS	PS	PM	PB	PVB	PVB	PVB
PM	NS	NVS	ZE	PVS	PS	PM	PB	PVB	PVB	PVB	PVB
PB	NVS	ZE	PVS	PS	PM	PB	PVB	PVB	PVB	PVB	PVB
PVB	ZE	PVS	PS	PM	PB	PVB	PVB	PVB	PVB	PVB	PVB

Search of Fuzzy Control Rules

For each value of error and change of error there are always 2 selected fuzzy sets for error and 2 selected fuzzy sets for change of error while the other are equal zero (e.g. if an error is located in level number 3, two fuzzy sets are selected NM(f_5), NS(f_6), and if the change of error is located in level number 4, two fuzzy sets are selected NS(f_7), NVS(f_8). Therefore, 4 rules only can be applied which are represented by the intersection of 3rd and 4th rows with 4th and 5th columns in Table 2.

Fuzzy Reasoning

In this application, we have applied the method of Mamdani's minimum operation discussed above. In this method, the obtained control action is a fuzzy set, which requires a defuzzification strategy to obtain the crisp control action.

Defuzzification Strategy

In this application, we have applied the method of center of gravity which has been discussed above, and the crisp value is obtained by the following equation:

$$U_o = \frac{w_1 u_1 + w_2 u_2 + w_3 u_3 + w_4 u_4}{w_1 + w_2 + w_3 + w_4}$$

A suitable scaling factor is introduced to convert the crisp control value from normalized discourse to the applied range of control signal (Dequantization).

Altering Scaling Factors

Quite simple schemes for altering the scaling factors to meet various performance criteria can be devised. During startup the terminal voltage must be increased to its operating point by increasing the exciter input. The terminal voltage increases slowly at first, and then rises abruptly. In order to prevent overshoot and oscillations in the terminal voltage, the controller gain must be kept low during this period, so that only small changes in the exciter input are made for large changes in terminal voltage. However, if this low gain is retained once the operating point of the terminal voltage is reached, small, low frequency oscillations in the terminal voltage result, due to the low sensitivity of the controller to fluctuations in the terminal voltage. The controller gain consequently needs to be increased. (AFLC) was designed with the error and change of error of the terminal voltage as inputs and the exciter voltage as output. We used the following scheme to automatically increase the controller gain once the terminal voltage was reached by altering the scaling factors for the error and the change of error. The performance measure is the average of the squared error over the previous three sampling time. At sampling time, k, a scaling factor modifier, C_k, is calculated as a function of the performance measure, P_k, according to the set of linguistic rules:

If P_k is VERY LARGE then C_k is VERY SMALL
If P_k is LARGE then C_k is SMALL
If P_k is MEDIUM then C_k is MEDIUM
If P_k is SMALL then C_k is LARGE

The scaling factors for the error (GE) and change of error (GCE) are then calculated via:

$$GE_k = C_k * GE_o$$
$$GCE_k = C_k * GCE_o$$

where GE_o, GCE_o, are fixed initial values.

These rules for C_k can be implemented in a fuzzy way, or crisp value of C_k for different ranges of P_k. The rules have the effect of increasing the controller gain by increasing the scaling factors. As the average squared error decreases, the process is maintained around its set point.

Altering Fuzzy Sets Shapes

The tuning mechanism is to alter the shapes of the fuzzy sets defining the meaning of linguistic values. The fuzzy sets definitions are not arbitrary but are chosen to reflect the meaning of the linguistic values taken by the variables. While this is certainly true for the broad shapes of the sets, small modifications can still be made without endangering the underlying linguistic meaning. The controller in that simple algorithm has been devised to alter the set definitions in response to a performance measure, which is the average of the squared error over the previous three sampling time.

This method relies on decreasing the width of the fuzzy set definitions by rewriting the equations of the triangle shaped function as $f_i = f(x,c$ where c is the average of the squared error over the previous three sampling time.

TURBO-GENERATOR SYSTEM

The system considered in this paper consists of a turbo-generator unit connected to a large power system by transformer and two parallel transmission lines. The nonlinear mathematical model equations of synchronous generator are established in Reference 2 and 3, as are the assumptions contained in their derivation. The transmission system may be represented by lumped series resistance and reactance, which can be combined with the impedance of the generator transformer. A thyristor exciter is used because it gives very fast control action. The generator is represented by 7th order nonlinear mathematical model, and it is driven by a three stage steam turbine with reheat, the turbine can be represented by 6th order nonlinear mathematical model, each stage consists of a single-time constant element. The re-heater and valve servo-mechanism are also described by first-order transfer functions. A 13th order nonlinear mathematical model was used to describe the turbo-generator for the tests reported here.

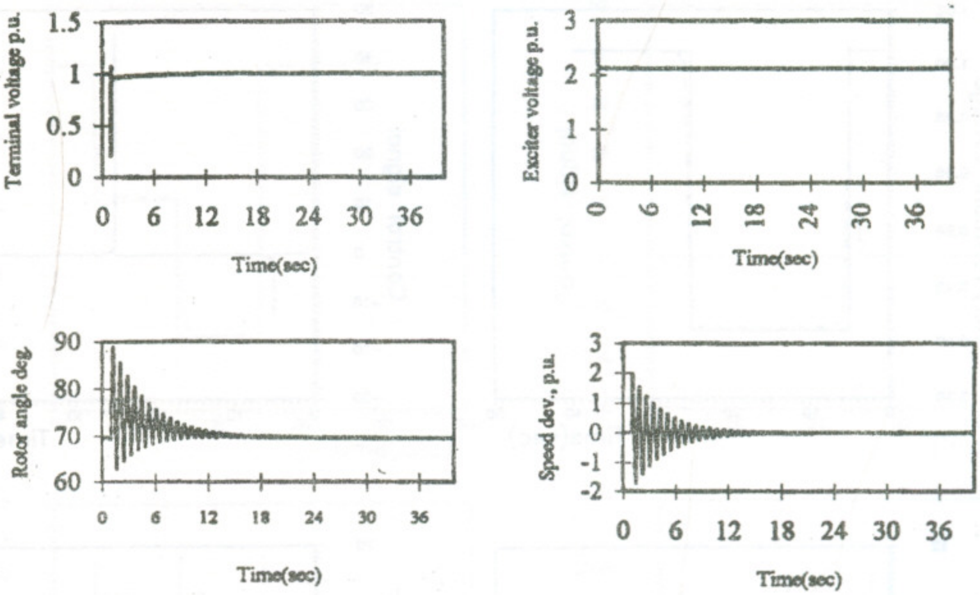
SIMULATION RESULTS

The following results indicate the behavior of the non-linear SISO turbo-generator system with the adaptive fuzzy logic controller. The non-linear digital simulation of the plant has been adjusted to operate at certain operating point described in terms of active and reactive powers at machine terminals. The principal input to the controller is taken as the sampled terminal voltage V_t, and the reference voltage V_r, with a sampling period of 20 m. sec. The controller in turn computes the control signal which should be applied to the excitation input. Figure 6 shows the open loop simulation of the turbo-generator under two tests, short circuit test and line outage test at the end terminals of the generator. From the figure, we show that the terminal voltage, the speed deviation, and the rotor angle reach their steady states 18 sec after the disturbance had occurred. A13th order non-linear model of a turbo-generator was simulated and test results were obtained by subjecting the system to the following disturbances:

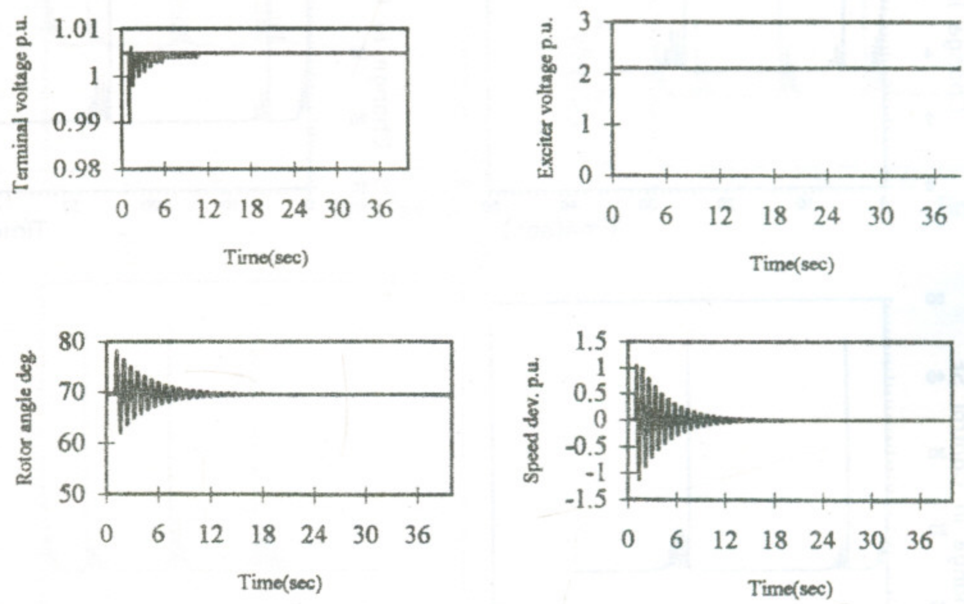
(1) Terminal Voltage Reference Disturbance

It is necessary to see how the machine responds to a change of the reference voltage. The reference voltage is reduced and/or increased by 10% step from its steady state value, and returns to the steady state of the terminal voltage after 15 seconds, at operating point P_t =0.8 p.u , Q_t =0.2 p.u.

Figure 7, shows that, when using the AFLC based on the changing in the scaling factors, the terminal voltage follows the reference voltage without any overshoot, with small rise time. An increase in the scaling factors will increase the inputs of the controller to compensate for the changes in the terminal voltage. Figure 8 indicates the system response when we add another disturbance to the reference voltage at t=15 sec. Also, we show that the terminal voltage follows the reference voltage without any overshoot, with small rise time and increasing in the scaling factors. This disturbance can reach 40% from the steady state of the terminal voltage while the output can track it.



(a) Short Circuit Test



(b) Line Outage Test

Figure 6 Open loop simulation of a turbogenerator system

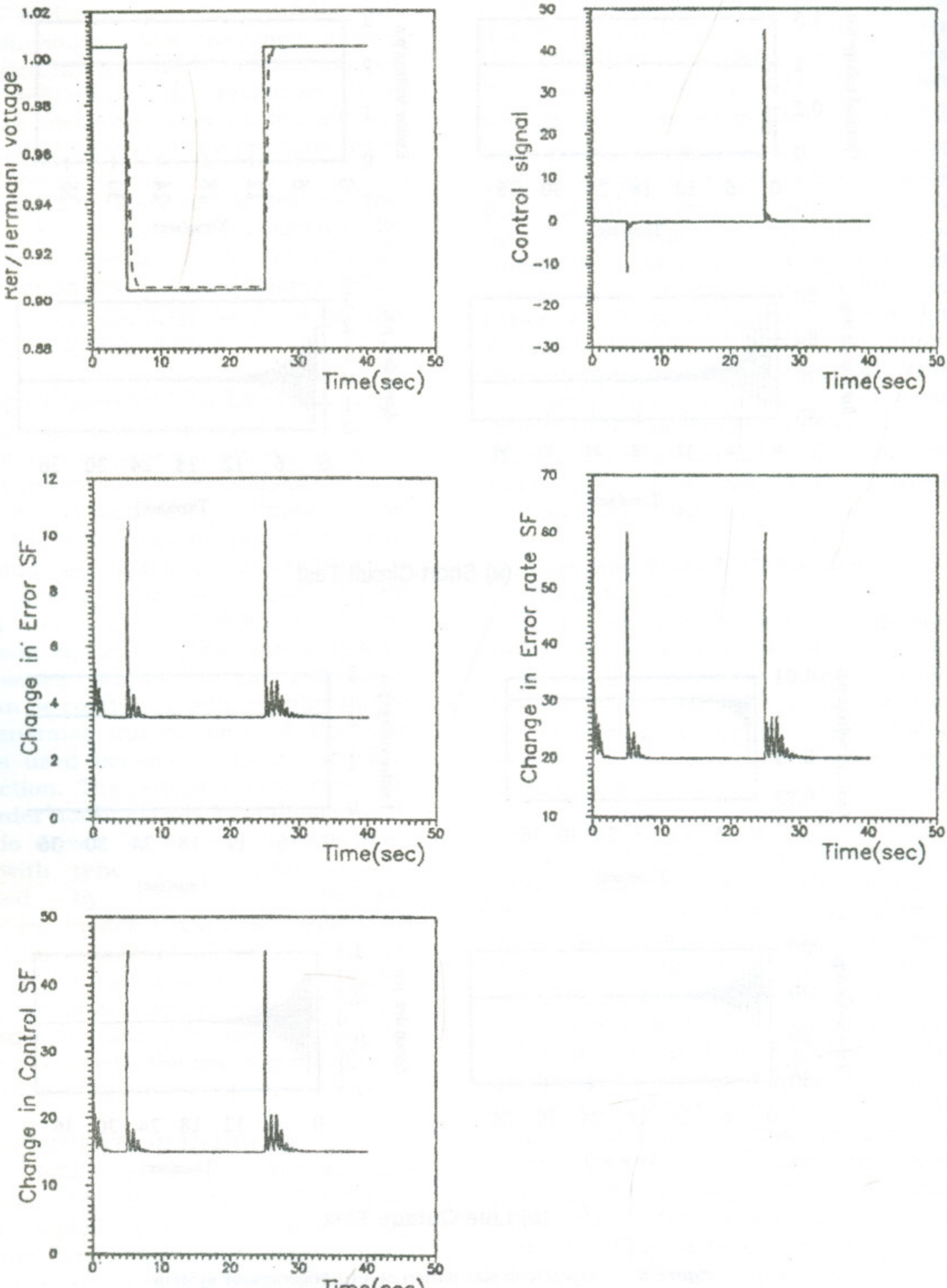


Figure 7 Terminal voltage reference disturbance test (10% from SS)

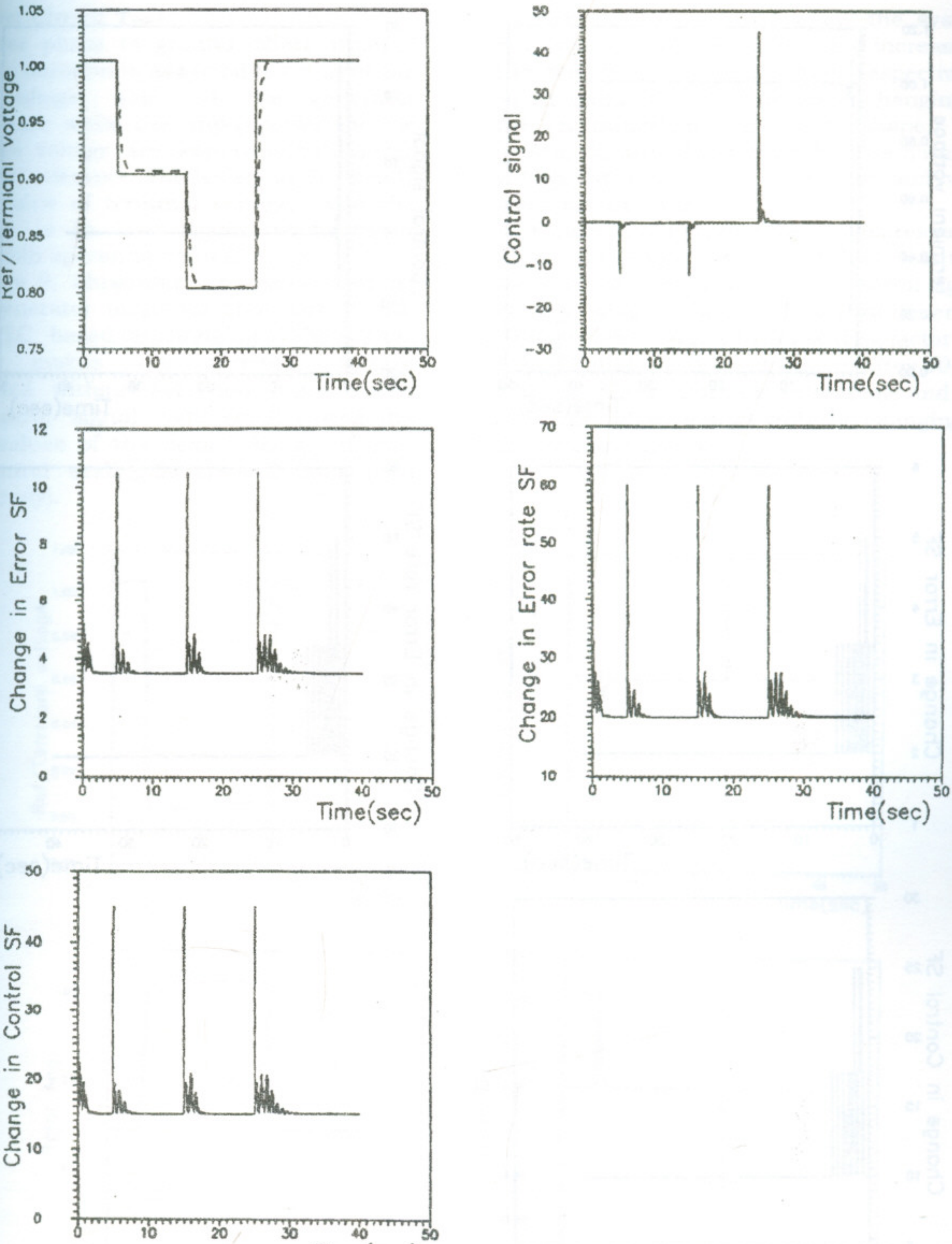


Figure 8 Terminal voltage reference disturbance test (20% from SS)

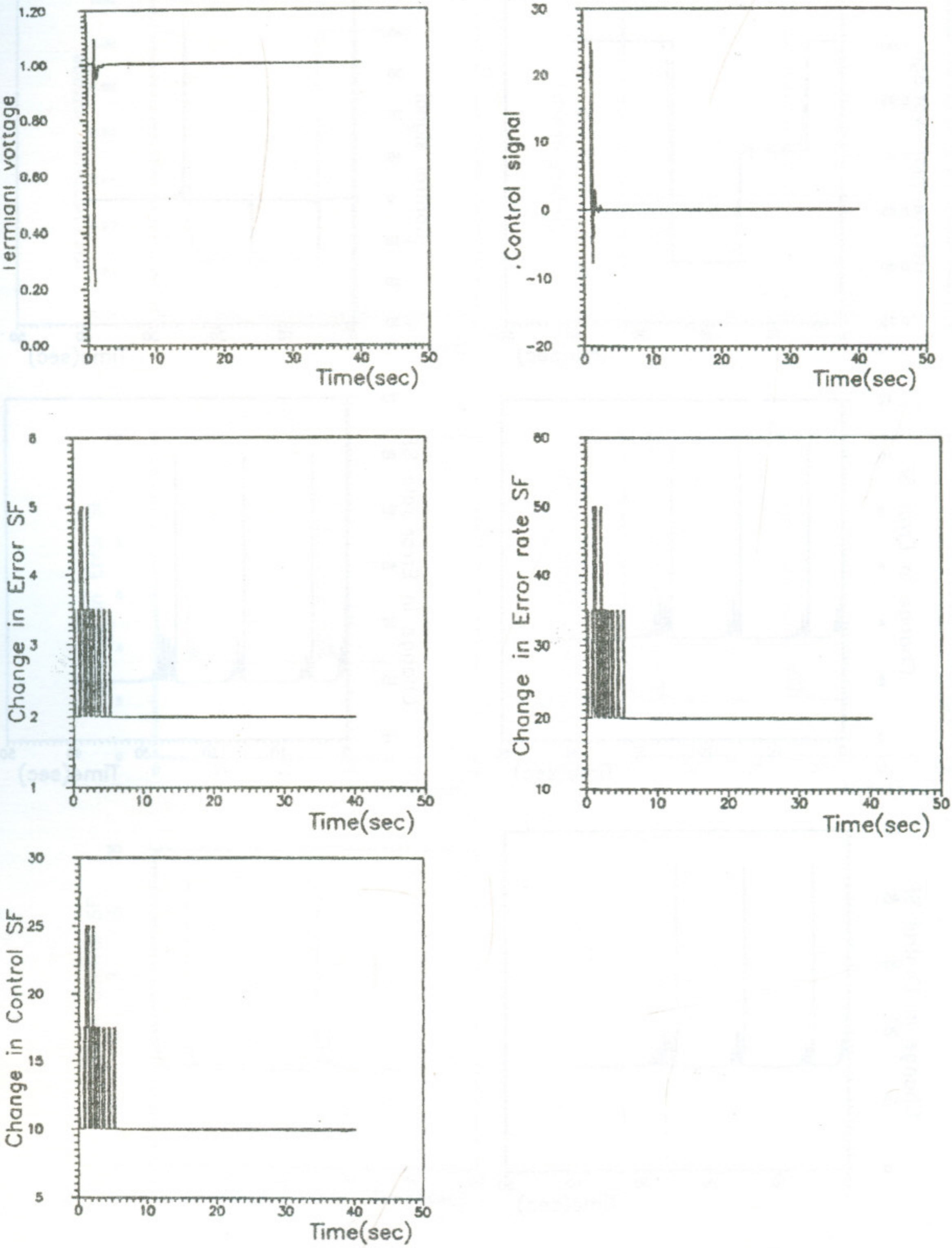


Figure 9 Short circuit test using fuzz way

(2) Short Circuit Test

A three phase to ground short circuit of 100 ms duration is assumed to occur at the high voltage side of the generator transformer while the input power and the reference voltage are kept constant (in this case the reference voltage equal the steady state value of terminal voltage). Also the machine is in the lagging power factor region with operating point (0.8,0.2).

Figure 9, illustrates the response of the turbo-generator under the short circuit test. The AFLC based on changing in the scaling factors makes the terminal voltage responded without overshoot and makes the control signal very small (using the initial values of the error, change of error and control scaling factors as 2, 20, and 10 respectively).

Figures 10 and 11 show the system response to 10% decrease and increase in the reference terminal voltage respectively, when using the AFLC based on changing in the membership functions shape. The system output follows the reference terminal voltage without any overshoot and with smalling rise time.

Figure 12 illustrates the system response under the short circuit test. It is clear that there is no overshoot and the control signal is very small. The initial value of the error, change of error and control scaling factor are 2.5, 45 and 10 respectively. Figures 10, 11 and 12, show that the rotor angle and the speed deviation change with the changing in the terminal voltage.

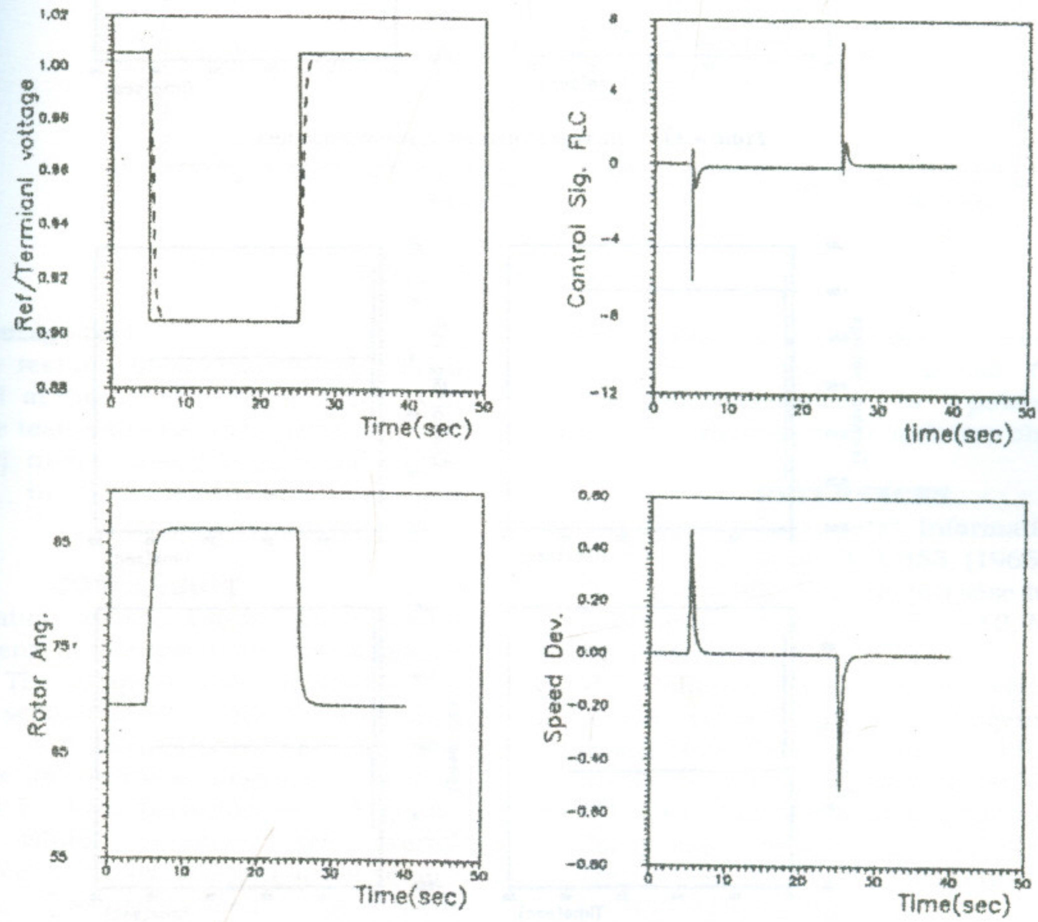


Figure 10 Decreamented reference voltage test

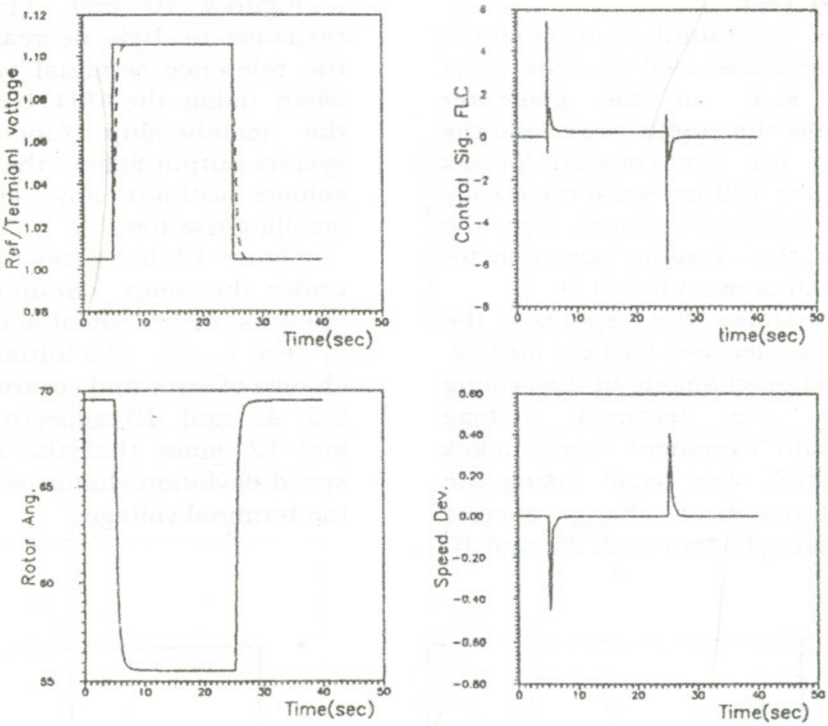


Figure 11 Increamented reference voltage test

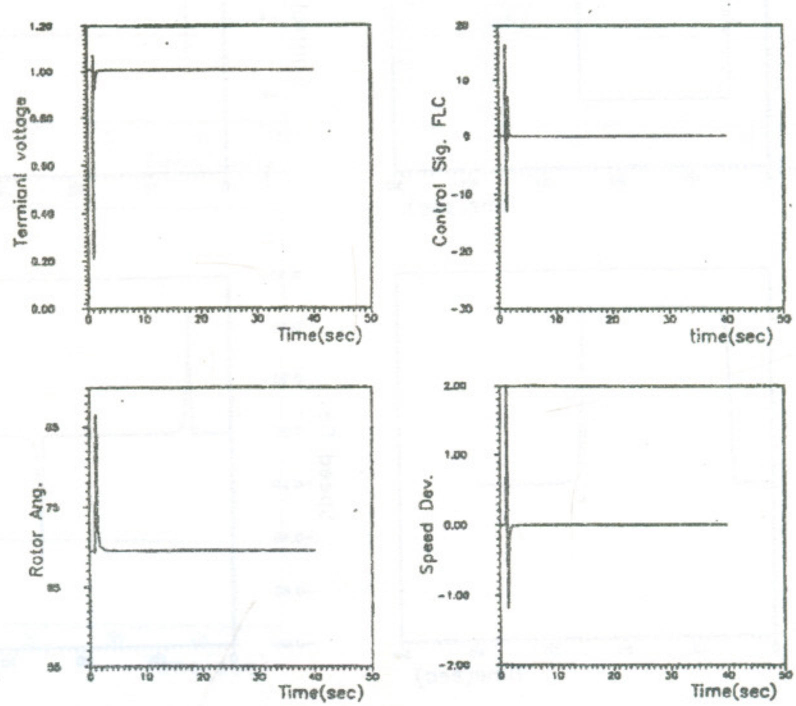


Figure 12 Short circuit test

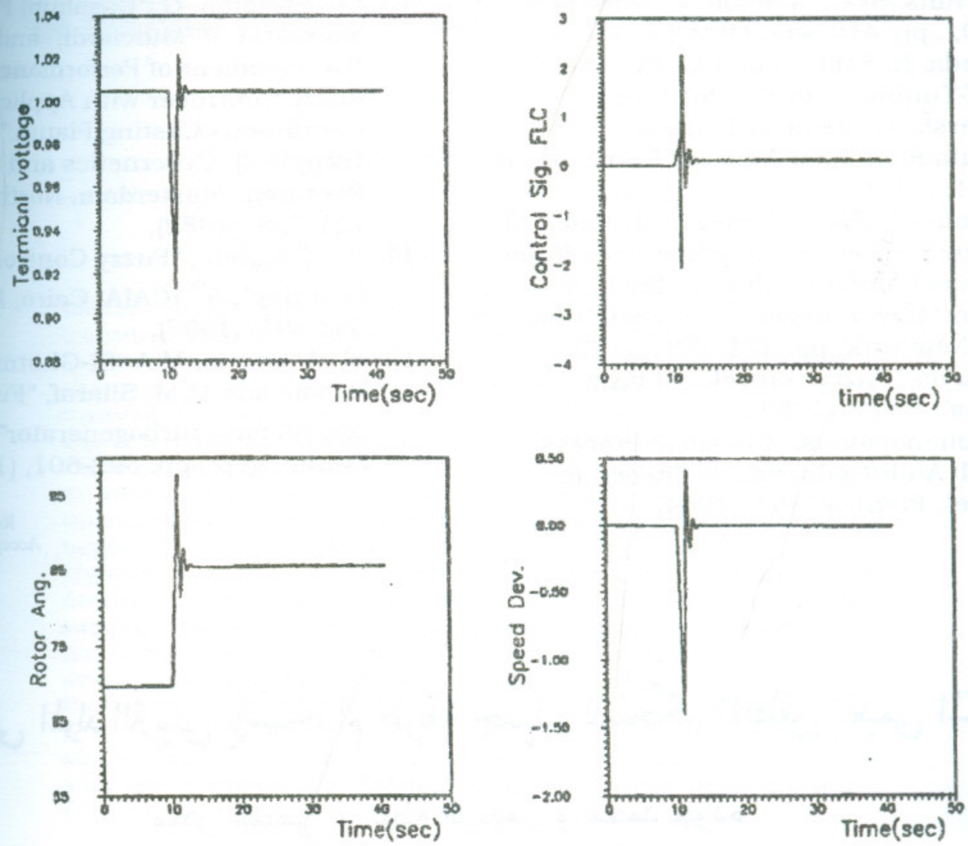


Figure 13 Line outage test

(3) Line outage test

In this test one of two transmission lines is outaged at the time t= 10 sec. Figure(13), shows the test results at the operating point (0.8 , 0.2) under using AFLC based on the changing in the membership functions shape.

CONCLUSION

Simulation results showed the expected improvement in control with this adaptive schemes. The adaptive mechanisms are to alter the scaling factors and the shapes of fuzzy set. Any adaptive controller, in order to improve its control strategy, must be able to assess its own performance. A global criterion, which measures the overall performance such as integral of the square error (ISE) has been used. The system performance has been evaluated and results show a good performance and robustness over a wide range of operating conditions. The results obtained affirmed that the developed algorithm is powerful for achieving tracking and regulation objectives.

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التحكم فى المولد التربينى بإستخدام طريقة جديده للمتحكم المنطقى الغيمى المتلائم

ماهر الغتمى ، نبيلة الربيعى و محمد جوده
قسم هندسة نظم التحكم و القياسات – جامعة المنوقية

ملخص البحث

يقوم هذا البحث بإختبار سلوك المولد التربينى أحادى الدخل أحادى الخرج المحمل بموصل لانــهائى عن طريق خطى نقل ومحول وذلك عندما يتم إستبدال منظم الجهد التقليدى بمتحكم منطقى غيمى متلائم.
وتعتمد الطريقة الجديدة على تغيير شكل دالة العضوية الخاصة بكل من الخطأ (الخطأ بين خرج النظام ونقطة مرجع معينة)، والتغير فى الخطأ، وإشارة التحكم عن طريق تغيير عرض هذه الدوال تبعاً للتغير فى آداء النظام. ويقوم هذا المتحكم بموائمة النظام للتغيرات الديناميكية الخطية واللاخطية التى تحدث على أطرافه أو فى داخله.
وقد أظهرت النتائج أن هذه الطريقة للمتحكم المنطقى المتلائم الغيمى يجعل خرج النظام يتبع نقطة مرجع معينه. وأيضاً يصحح من خرج النظام عندما تحدث أعطال على أطراف الآلة مثل دائرة القصر أو فصل أحد خطى النقل.