Paper

Braking Resistor Switching By Genetic Algorithm Optimized Fuzzy Logic Controller In Multi-Machine Power System

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Fuzzy logic has been gaining increasing acceptance in control applications during the past few years. Usually, the membership functions and control rules of fuzzy logic controller are determined by trial and error which is cumbersome and time consuming. Therefore, to surmount such a drawback, this paper makes use of the Genetic Algorithm (GA) technique for optimal tuning of the parameters of the Fuzzy Logic Controller (FLC) used for the switching of the thyristor controlled braking resistor to improve power system transient stability. The braking resistor is installed at each generator bus, where rotor speed of the generator is measured to determine the firing-angle of the thyristor switch. By controlling the firing-angle of the thyristor, braking resistor controls the accelerating power in generators and thus improves the transient stability. The effectiveness of the proposed method has been demonstrated by considering both balanced (3LG: Three-phase-to-ground) and unbalanced (1LG: Single-line-to ground, 2LG: Double-line-to ground and 2LS: Line-to-line) faults at different points in a multi-machine power system.

Keywords: braking resistor, transient stability, fuzzy logic, genetic algorithm, balanced fault, unbalanced faults

1. Introduction

A Braking Resistor (BR) is a very effective device for transient stability control. It can be viewed as a fast load injection to absorb excess transient energy of an area which arises due to severe system disturbances. Besides, with the recent development of power electronics technology, replacing circuit breaker with the semiconductor device is becoming feasible. Several thyristor-based control techniques [1]~[4] have been proposed in the literature for the switching of the braking resistor. Again, fuzzy logic is getting increasing emphasis day by day in control applications. In [5][6] we proposed two works for the fuzzy logic switching of the thyristor controlled braking resistor. However, the membership functions and control rules were determined by trial and error which is a tedious and time consuming task. For efficiency, an optimal design of control rules and membership functions of the fuzzy controller is desired.

Genetic algorithms are search procedures and optimization techniques which are based on the mechanics of natural selection and genetics [7]. They are often used as a parameter search technique to find near optimal solutions. Recently, there have been some studies using GA to design membership functions [8], while other studies have used GA to design control rules for FLC [9]. However, these designs of FLC still require the use of an expert's experience, for example, to design control rules for the former or membership functions for the latter.

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In this paper, we have applied the genetic algorithm technique for optimal tuning of both the membership functions and control rules simultaneously for the fuzzy controller. Another salient feature of this work is that a multi-machine model system instead of single machine systems as used in the previous works [5][6] is considered. The simulation is implemented by using EMTP (Electro-Magnetic Transients Program). Through the simulation results of both balanced and unbalanced faults at different points, the effectiveness and validity of the proposed method are confirmed. Therefore, it can be concluded that the proposed fuzzy controller designed by the GA technique is an excellent and effective method for transient stability improvement.

2. Model System

Fig. 1 shows the 9-bus power system model [10] used for the simulation of transient stability. The system model consists of two synchronous generators (G1 and G2) and an infinite bus connected to one another through transformers and double circuit transmission lines. In the figure, the double circuit transmission line parameters are numerically shown in the forms R+jX (jB/2), where R, X and B represent resistance, reactance and susceptance respectively per phase with two lines. The braking resistors are connected to each of the generator bus through the thyristor switching circuit, as shown in Fig. 2. The conductance values of the braking resistors are selected from the viewpoint that they can absorb an amount of power equal to the rated capacity of the machines at full conduction, if the voltage across the resistor is about 1.0 pu. The system base is 100MVA

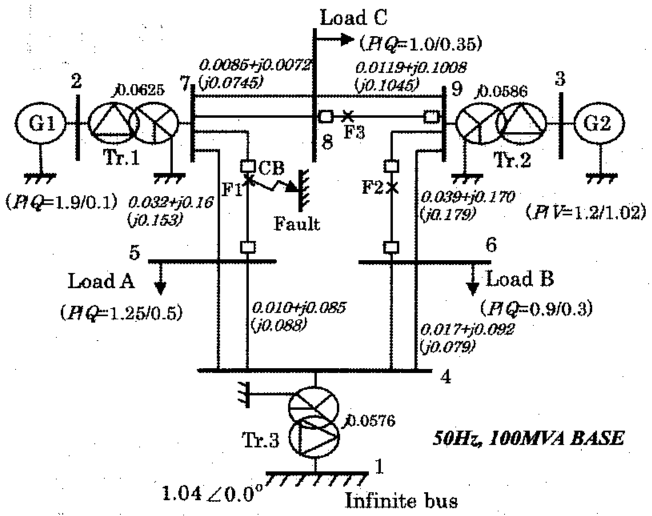


Fig. 1. 9-Bus Power System model

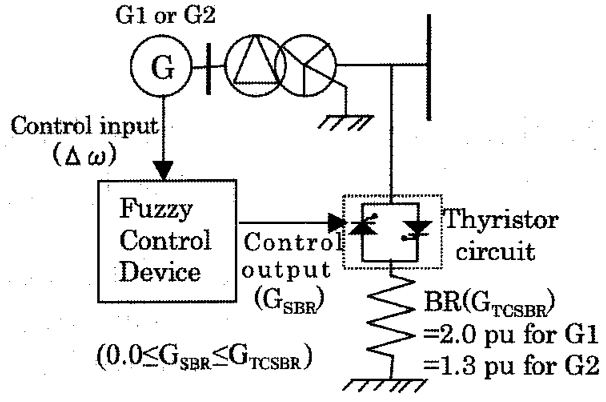


Fig. 2. BR with thyristor switching circuit

Table 1. Generator parameters

	G1	G2
MVA	200	130
r_a (pu)	0.003	0.004
x_a (pu)	0.102	0.078
X_d (pu)	1.651	1.220
X_q (pu)	1.590	1.160
X'_d (pu)	0.232	0.174
X'_q (pu)	0.380	0.250
X''_d (pu)	0.171	0.134
X''_q (pu)	0.171	0.134
$T'do$ (sec)	5.900	8.970
$T'qo$ (sec)	0.535	1.500
$T''do$ (sec)	0.033	0.033
$T''qo$ (sec)	0.078	0.141
H (sec)	9.000	6.000

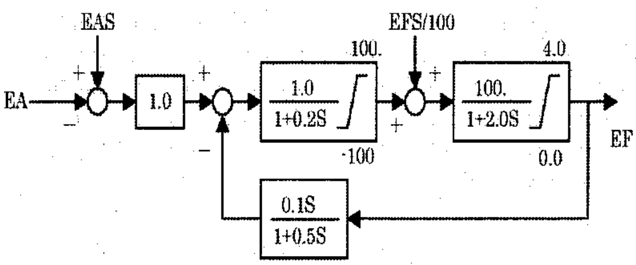


Fig. 3. IEEJ AVR model (LAT=1)

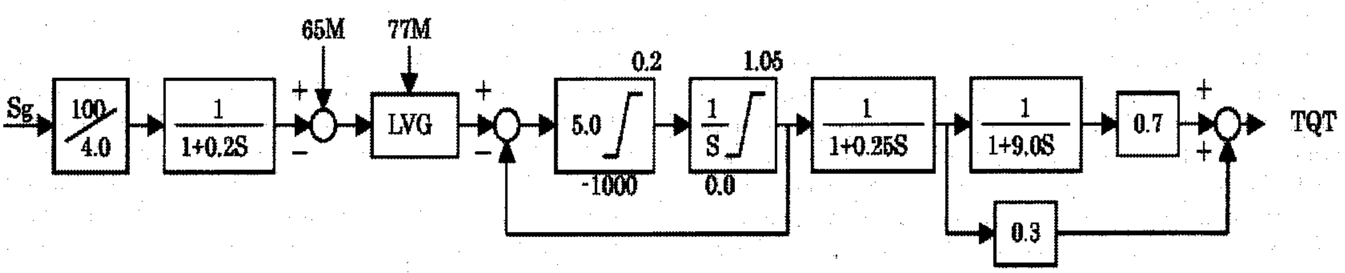


Fig. 4. IEEJ GOV model (LPT=1)

and the capacities of generator 1 and generator 2 are 200MVA and 130MVA respectively. Therefore, the conductance values of the braking resistors are considered 200/100=2.0 pu and 130/100=1.3 pu for generator 1 and generator 2 respectively. The BR will be switched in following a fault clearing and the switching condition of BR is such that when deviation of speed of the generator is positive, BR is switched on the generator terminal bus. On the other hand, when deviation of speed is negative and also in the steady state, BR is removed from the generator terminal bus by the thyristor switching circuit. The IEEJ AVR (Automatic Voltage Regulator) and GOV (Governor) control system models as shown in Figs. 3 and 4 respectively have been included in the simulation [11].

In the simulation study, three cases have been considered. First one is the fault near generator 1 at point F1, second one is near generator 2 at point F2 and third one is at point F3. In all of the three cases the fault occurs at 0.1 sec, the circuit breakers (CB) on the faulted lines are opened at 0.2 sec and at 1.0 sec the circuit breakers are closed. Time step and simulation time have been chosen as 0.00005 sec and 10.0 sec respectively. The various parameters of the generators used for the simulation are shown in Table 1.

3. Design of Fuzzy Logic Controller by Genetic Algorithm

3.1 Fuzzy Controller Design

3.1.1 Fuzzification For the design of the proposed FLC, generator speed deviation, $\Delta\omega$, and conductance value of BR, G_{SBR} $(0.0 \leq G_{\mathrm{SBR}} \leq G_{\mathrm{TCSBR}})$, are selected as the input and output respectively. We have selected the triangular membership functions as shown in Fig. 5 in which the linguistic variables NE, ZO and PO stand for Negative, Zero and Positive respectively. The four points marked as A, B, C and D are to be optimized by the genetic algorithm.

The equation of the triangular membership function used to determine the grade of membership values is as

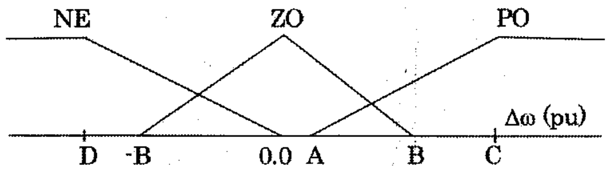


Fig. 5. Membership function of $\Delta\omega$

follows [12].

$$\mu_A(\Delta\omega) = 1/b(b - 2|\Delta\omega - a|) \cdots\cdots (1)$$

Where $\mu_A(\Delta\omega)$ is the value of grade of membership, 'b' is the width and 'a' is the coordinate of the point at which the grade of membership is 1, $\Delta\omega$ is the value of the input variable i.e. deviation of speed.

3.1.2 Fuzzy rule base A fuzzy controller typically follows the "IF-THEN" rules. In this work, we have developed 3 simple control rules corresponding to 3 linguistic variables NE, ZO and PO of the speed deviation, $\Delta\omega$, for the fuzzy controller design. These are as follows:

(i) If $\Delta\omega$ is NE, Then G_{SBR} is 0.0

(ii) If $\Delta\omega$ is ZO, Then G_{SBR} is 0.0

(iii) If $\Delta\omega$ is PO, Then G_{SBR} is $0.0 \leq G_{SBR} \leq 2.0$ (for G1) or $0.0 \leq G_{SBR} \leq 1.3$ (for G2).

The rules (i) and (ii) are developed easily from the viewpoint of practical system operation. Because in Section 2, it is explained that when deviation of speed is negative and also in the steady state, braking resistor will not be used. Hence, the conductance value is zero for that condition. Therefore, in rules (i) and (ii) we have directly used the values of G_{SBR} as zero and only in rule (iii) the values of G_{SBR} (for both G1 and G2) are to be optimized by the genetic algorithm.

3.1.3 Inference mechanism For the inference mechanism of the proposed fuzzy logic controller, Mamdani's method [12] has been utilized. According to Mamdani, the degree of conformity, Wi, of each fuzzy rule is as follows:

$$Wi = \mu_{Ai}(\Delta\omega) \cdots\cdots (2)$$

Where $\mu_{Ai}(\Delta\omega)$ is the value of grade of membership and i is rule number.

3.1.4 Defuzzification The Center-of-Area method is the most well-known and rather simple defuzzification method which is implemented to determine the output crispy value (i.e. the conductance value of the braking resistor, G_{SBR}). This is given by the following expression.

$$G_{SBR} = \sum WiCi / \sum Wi \cdots\cdots (3)$$

where Ci is the value of G_{SBR} in the fuzzy rules.

3.2 Genetic Algorithm Development Genetic algorithms are search procedures and optimization techniques based on the mechanics of natural selection and natural genetics. Before a GA is applied, the optimization problem should be converted to a suitably described function called "Fitness Function." It represents a performance of the problem. The higher the fitness value, the better the system's performance.

In this paper, the integral of the absolute value of the speed deviation of the generator is selected as the objective function. Therefore, the objective function, J, is expressed simply as

$$J = \int_0^T (|\Delta\omega_1| + |\Delta\omega_2|)dt \cdots\cdots (4)$$

which is to be minimized and where T is the simulation time of 10.0 sec, $\Delta\omega_1$ and $\Delta\omega_2$ are the speed deviations of generators 1 and 2 respectively. The corresponding fitness function, Fit, is given by:

$$Fit = \frac{1}{J} \cdots\cdots (5)$$

To apply the GA technique in this work, at first 30 sets of individuals or chromosomes each consisting of 6 discrete real-coded genes are generated as the initial population from the point of view of system knowledge. An example of a group of the genes in a chromosome is shown in the following:

$$[0.00028, 0.00112, 0.0026, 0.00292, 1.80000, 1.10000].$$

The first through fourth genes in the chromosome are the elements of membership functions i.e. the values corresponding to points A, B, C and D in Fig. 5 and last two are the elements of control rule i.e. the values of G_{SBR} in rule (iii).

Next the GA involves two basic steps: i) the system is simulated to calculate the fitness function and ii) three operations are performed: Selection or Reproduction, Crossover and Mutation to produce the next generation of individuals.

Selection is the process of carrying old individuals through into a new population, depending on the fitness value. In this work, the roulette wheel selection [13] is applied for reproduction operation.

Crossover is a genetic operation that offsprings (new chromosomes) are produced by exchanging the genes between two individuals (parents). In this work, we have used the Single Point Crossover technique [13].

Mutation is a genetic operator that alters the value of a point which is randomly selected in an individual. A technique called non-uniform mutation, taken from Ref. (13), is used to improve the performance of the algorithm. The non-uniform mutation operator is defined as follows: if $s_v^t = [v_1, \ldots, v_m]$ is a chromosome (t is the generation number) and the element v_k is selected for this mutation, the result is a vector $s_v^{t+1} = [v_1, \ldots, v'_k, \ldots, v_m]$, where

$$V'_k = \begin{cases} v_k + \Delta(t, UB - v_k) & \text{if a random digit is 0,} \\ v_k - \Delta(t, v_k - LB) & \text{if a random digit is 1,} \end{cases}$$

and LB and UB are lower and upper domain bounds of the variable v_k. The function $\Delta(t, y)$ returns a value in the range $[0, y]$ such that the probability of $\Delta(t, y)$ being close to 0 increases as t increases. This property

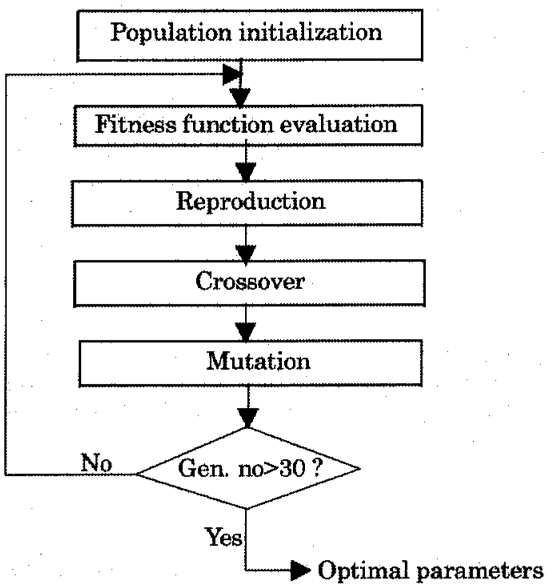


Fig. 6. Evolution procedure of GA

Table 2. Genetic algorithm parameters

Population size	30
Probability of crossover	0.75
Probability of mutation	0.01
Maximum generation	30

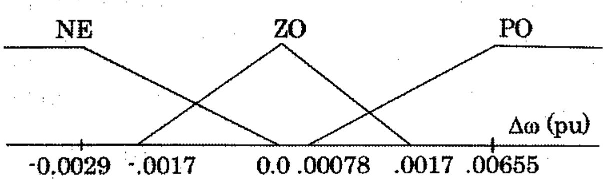


Fig. 7. Membership function of $\Delta\omega$ by GA tuning

causes this operator to search the space uniformly initially (when t is small), and very locally at later stages; thus increasing the probability of generating the new number closer to its successor. We have used the following function for $\Delta(t, y)$:

$$\Delta(t, y) = y.\{1 - r^{(1-t/T)^b}\} \quad \cdots\cdots\cdots\cdots\cdots\cdots \quad (6)$$

where r is a random number from $[0 \ldots 1]$, T is the maximal generation number, b is a system parameter determining the degree of non-uniformity (we have used $b = 5$).

The above two steps are repeatedly applied until convergence condition is satisfied, producing a near optimal parameter set. With convergence condition, if the generation number is 30, the genetic operation is stopped. The evolution procedure for the GA is shown in Fig. 6.

In order to improve convergence of the GA, a procedure called elitism [7] is used which guarantees that the fittest individual so far obtained in the search is retained and used in the following generation, and thereby ensuring no good solution already found can be lost in the search process. The various genetic algorithm parameters selected in this work are shown in Table 2.

Finally, the membership functions and control rules of the optimal FLC as developed by the GA are shown in

Table 3. Fuzzy rule table by GA tuning

$\Delta\omega$	G_{SBR} (pu)
NE	0.0
ZO	0.0
PO	2.0 for G1 1.3 for G2

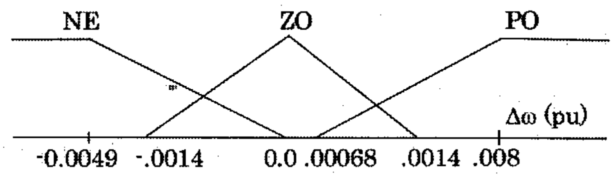


Fig. 8. Membership function of $\Delta\omega$ by trial and error

Table 4. Fuzzy rule table by trial and error.

$\Delta\omega$	G_{SBR} (pu)
NE	0.0
ZO	0.0
PO	2.0 for G1 1.3 for G2

Fig. 7 and Table 3 respectively. In this work, in order to understand the effectiveness of the GA based tuning, the performance of the fuzzy controller with the genetic algorithm based tuning is compared to that of with the trial and error based tuning. The best memebrship functions and control rules of the fuzzy controller determined by the trial and error method are shown in Fig. 8 and Table 4 respectively.

The firing control signal can be determined from the conductance value, G_{SBR}, and then sent to the thyristor switching unit to modify the real power absorbed by the braking resistor in the transient condition. The modelling of TCSBR (Thyristor Controlled System Braking Resistor) and method of calculting firing-angle from the output of the fuzzy controller are described in detail in Reference (5).

4. Simulation Results

4.1 GA Results Fig. 9 shows the maximum fitness value versus the generation number curve for the genetic algorithm. The fitness values are not normalized and are directly calculated from equation 5. The maximum fitness value was found to be 145.733276 at generation number 21. Therefore, the fuzzy parameters corresponding to this maximum fitness value at generation number 21 were taken as the optimal parameters which are already shown in Fig. 7 and Table 3. Fig. 10 shows the average fitness value corresponding to each generation. The average fitness in each of the 30 generation is most indicative of how well the GA is working. It is observed that at the first generation, the average fitness is fairly low. As the number of generation increases, the average fitness has an upward trend. As a whole, it is concluded that the proposed GA approach is effective for obtaining an optimal FLC.

4.2 Time Responses In order to show the effectiveness and validity of the proposed GA optimized

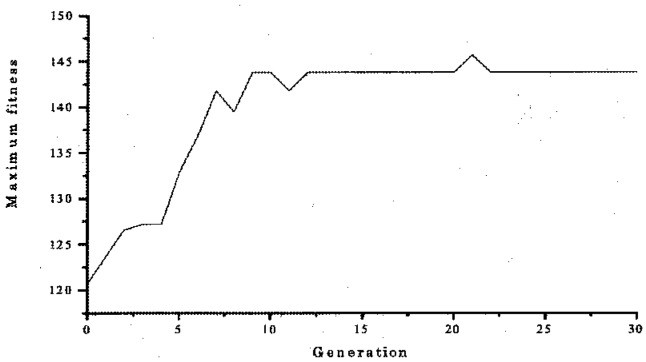


Fig. 9. Maximum fitness Vs generation number curve

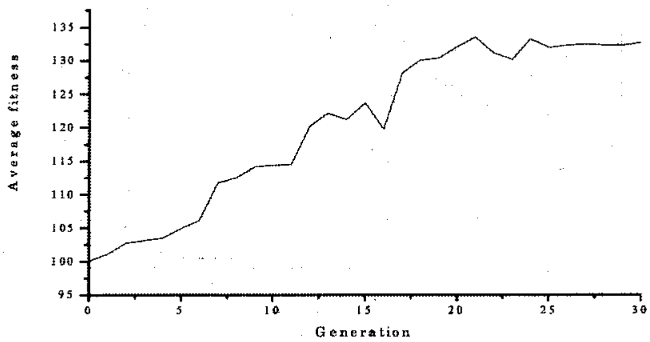
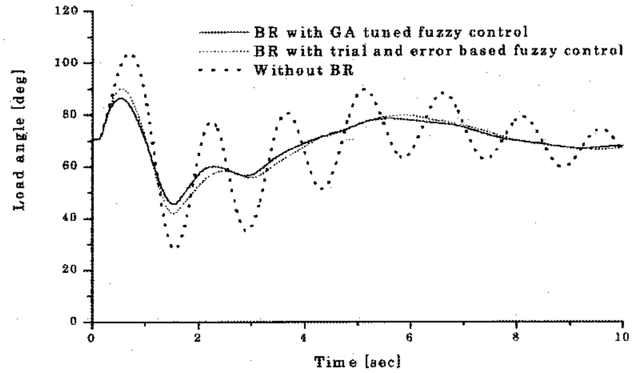
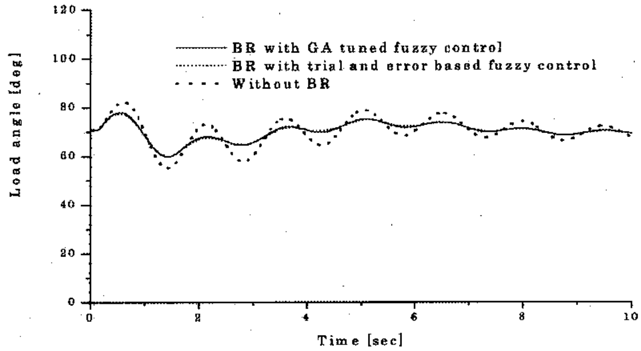


Fig. 10. Average fitness Vs generation number curve

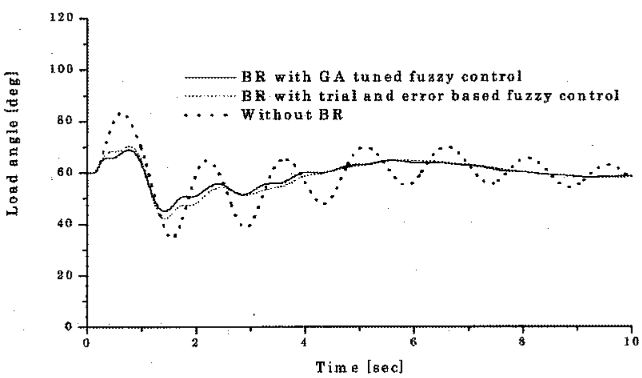


(a) 3LG fault

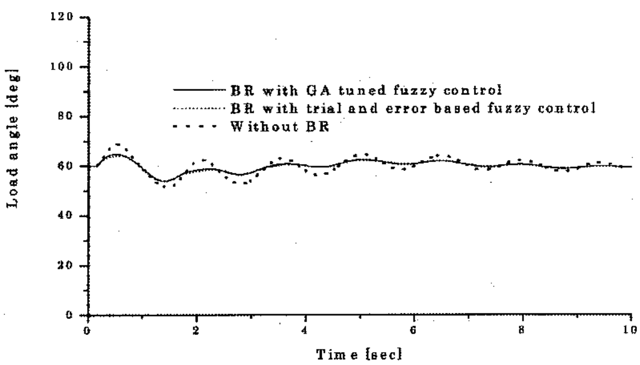


(b) 1LG fault

Fig. 11. Load angle responses for G1 with fault at point F1



(a) 3LG fault



(b) 1LG fault

Fig. 12. Load angle responses for G2 with fault at point F1

fuzzy logic controller, simulations have been carried out considering both balanced (3LG: three-phase-to-ground) and unbalanced (1LG: single-line-to-ground a-phase, 2LG: double-line-to-ground a-b phases and 2LS: line-to-line a-b phases) faults at three different points on the transmission lines. It is important to note here that the evaluation in the GA was carried out considering a 3LG fault at point F1 as the standard. Then the optimized fuzzy parameters obtained by the GA are used in the simulations of 1LG, 2LG, 2LS and 3LG faults at points F1, F2 and F3. Therefore, the fuzzy parameters were the same for all fault cases and fault points.

Figs. 11~16 show the load angle responses for generator 1 and generator 2 in case of 3LG and 1LG faults at points F1, F2 and F3. It is easily seen from these responses that because of the use of BR, the system is transiently stable for all the fault cases.

Again, it is observed that although the performance of the GA tuned fuzzy controller is almost the same as that of the trial and error based fuzzy controller in case of 1LG faults at all fault points, the performance of the GA tuned fuzzy controller is somewhat better than that of the trial and error based fuzzy controller in case of 3LG faults at all fault points from the point of view of the load angle deviation. However, the main advantage of using GA tuned controller is that optimal parameters are obtained just after completion of the running of the GA program in several hours but in the usual fuzzy controller parameters are obtained after a lot of trial and error which is obviously a time consuming and cumbersome task. It may even need several days to get the best parameters by trial and error. Moreover, the parameters obtained by trial and error method may or may not be optimal but the parameters determined by

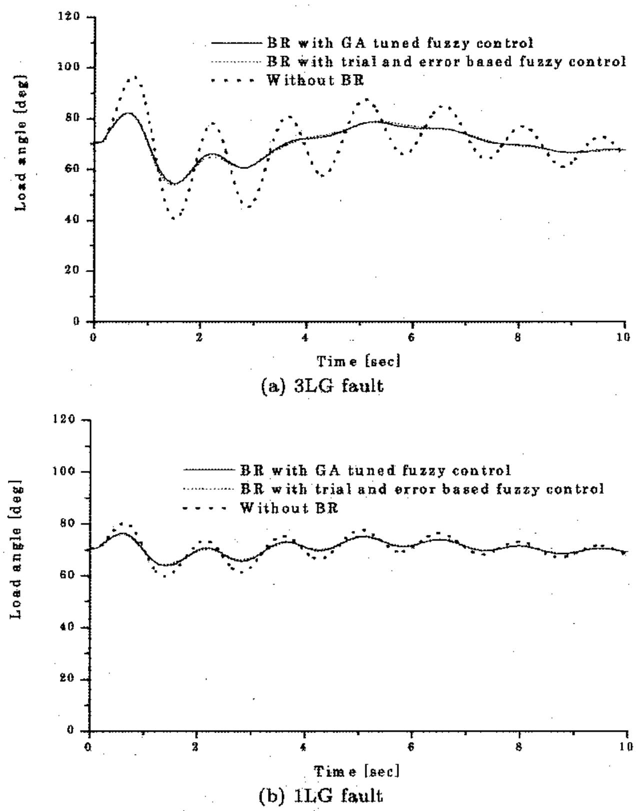


Fig. 13. Load angle responses for G1 with fault at point F2

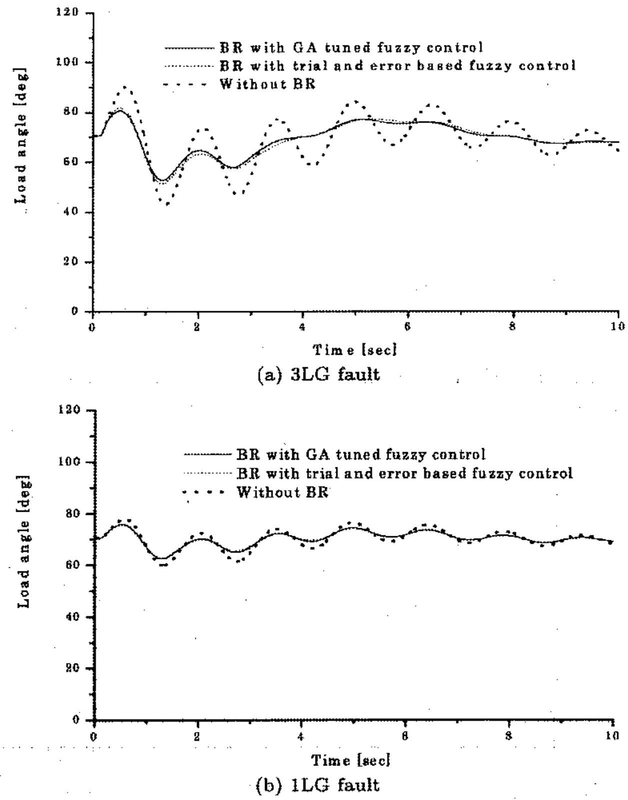


Fig. 15. Load angle responses for G1 with fault at point F3

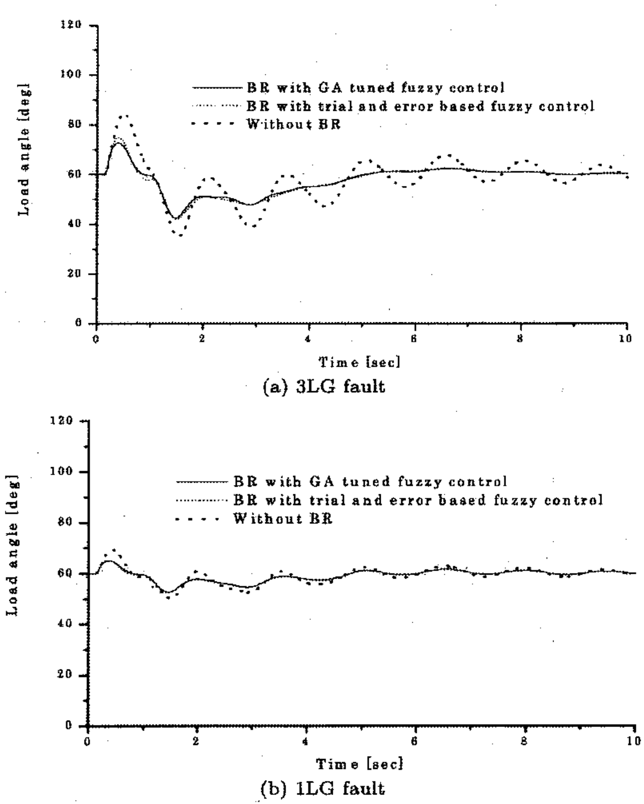


Fig. 14. Load angle responses for G2 with fault at point F2

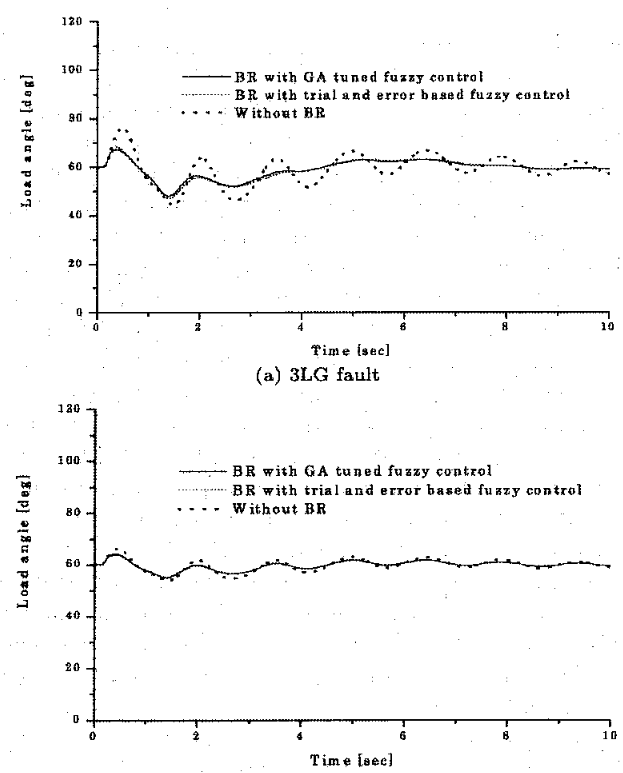


Fig. 16. Load angle responses for G2 with fault at point F3

the GA are always optimal or near optimal [7]. This fact corroborates the effectiveness of the GA based tuning.

However, it is observed for all fault cases in Figs. 11 and 12 that the deviations of load angle from their initial values are higher in generator 1 compared to those in generator 2. This is due to the fault point F1 near

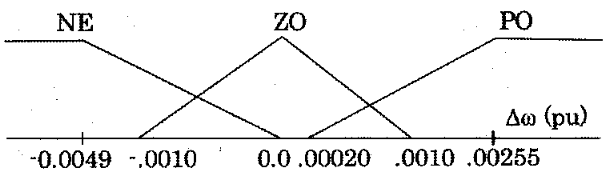


Fig. 17. Membership function of $\Delta\omega$ by rough tuning

Table 5. Fuzzy rule table by rough tuning

$\Delta\omega$	G_{SBR} (pu)
NE	0.0
ZO	0.0
PO	1.82 for G1 1.12 for G2

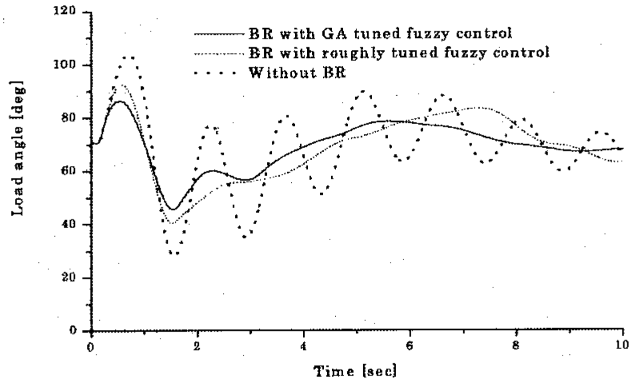


Fig. 18. Load angle responses for G1 with fault at point F1

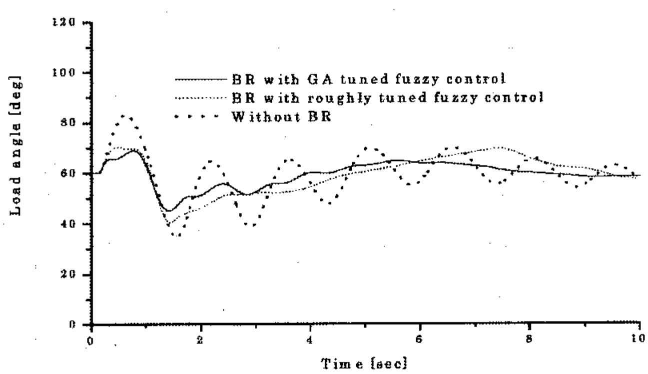


Fig. 19. Load angle responses for G2 with fault at point F1

generator 1 and hence, generator 1 is affected more than generator 2. Again, because of the fault at point F2 near generator 2, generator 2 is affected more compared to generator 1 as observed from Figs. 13 and 14. On the other hand, from Figs. 15 and 16 it is seen that both generators are affected almost equally because of the fault at point F3 which is far from both generators.

The specific feature of the fuzzy control is its robustness and in many cases, rough tuning of control parameters may give good control performance. But the performance of the GA tuned control parameters is always better and more effective. To understand this, in this work we have carried out simulations using a set of roughly tuned fuzzy parameters. The roughly tuned

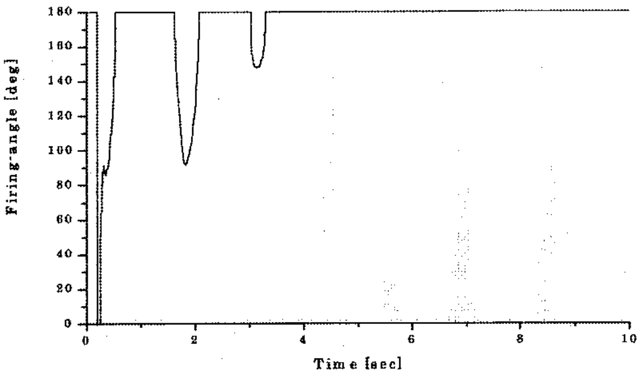


Fig. 20. Firing-angle response for BR 1

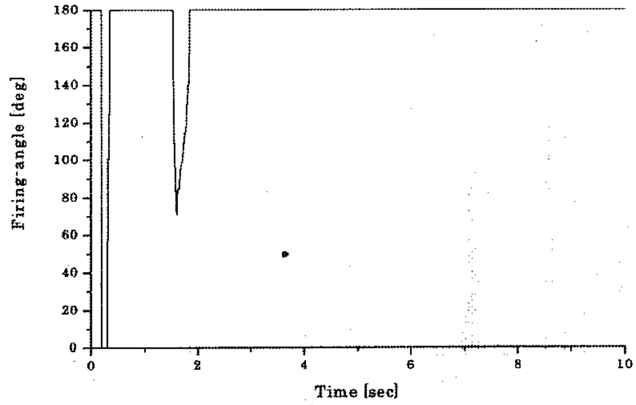


Fig. 21. Firing-angle response for BR 2

parameters are shown in Fig. 17 and Table 5. The simulation results are shown in Figs. 18 and 19 in case of 3LG fault at point F1. It is seen that although the performance of the roughly tuned parameters is good, the performance of the GA tuned parameters is more better than the performance using roughly tuned parameters. This is the major advantage of using GA tuned parameters which always give more better control performance and parameters are always optimal or near optimal.

In case of 2LG and 2LS faults at different points, we also observed good responses for GA tuned fuzzy controller although those are not shown in the paper.

Figs. 20 and 21 depict the firing-angle responses of the thyristor switch for phase 'a' for BR 1 and BR 2 respectively under balanced fault at point F2. The firing-angle varies from 0 degree to 180 degree according to the value of G_{SBR}. In section 2, it has been stated that when the power system becomes stable, BR is removed from the generator bus by the thyristor switching circuit. This signifies that in that case conductance, G_{SBR}, is zero and hence, firing-angle becomes 180 degree. Now, it is seen in both figures that after some variations from 0 degree to 180 degree, the firing-angle gets a constant value of 180 degree after about 3.3 sec in case of BR1 and after about 2.0 sec in case of BR2 and it remains the same upto 10.0 sec. This fact indicates that the system is in stable condition after about 3.3 sec.

Finally, in Figs. 22 and 23, it is shown the responses of three-phase dissipated power through BR 1 and BR 2 respectively in case of 3LG fault at point F2. In the

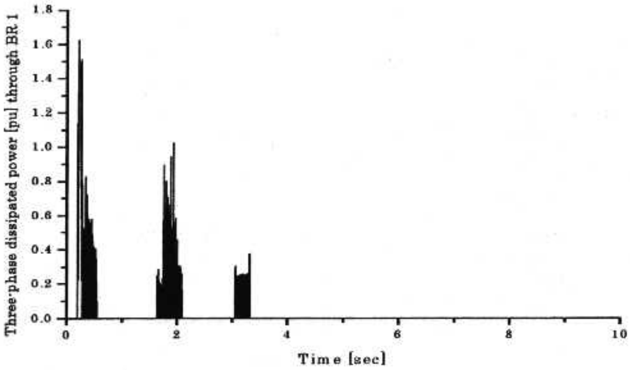


Fig. 22. Dissipated power response for BR 1

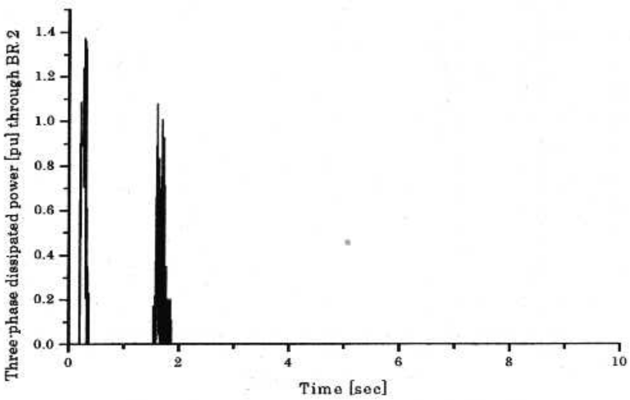


Fig. 23. Dissipated power response for BR 2

steady state of the power system, the power dissipation through BR is zero. Again, the amount of power to be dissipated through BR depends on the value of firing-angle. Therefore, it is observed in both figures that after some variations from 0.0 pu to about 2.0 pu (for BR 1) and 1.3 pu (for BR 2), the power dissipation becomes zero after about 3.3 sec for BR1 and after about 2.0 sec for BR2 and after that it is always zero upto 10.0 sec. This fact also indicates that the system is in stable condition after about 3.3 sec. It is seen that although the dissipated power of the braking resistor for generator 1 is within its capacity but the dissipated power of the braking resistor for generator 2 is beyond its capacity. But the braking resistor can consume the excessive power, because it occurs only for a very short transient period.

As a whole, from the point of view of the simulation results, two points are of paramount importance. First, the GA technique can optimally tune the fuzzy controller parameters. Second, the optimally designed fuzzy controller by the GA can effectively enhance the transient stability by switching the braking resistor. Therefore, it can be concluded that the proposed GA tuned fuzzy control scheme is an excellent and effective method to improve the transient stability for both balanced and unbalanced fault conditions.

5. Conclusion

In this paper, a Genetic Algorithm optimized fuzzy logic controller has been developed for the switching of the braking resistor to improve the transient stability of a multi-machine power system. The performance of the GA tuned fuzzy controller is compared to that of the trial and error based fuzzy controller. Simulation results clearly show the effectiveness and better performance of the GA tuned fuzzy controller compared with the conventional trial and error based fuzzy controller. Therefore, it can be concluded that the proposed optimal fuzzy logic controller designed by the GA technique provides an effective method of transient stability improvement.

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