International Journal of Applied Engineering Research
ISSN 0973-4562 Volume 10, Number 3 (2015) pp. 8267-8285

http://www.ripublication.com

Optimal Design Of Fuzzy Controller For Load Frequency Control Using Modified Cuckoo Search Algorithm

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Abstract

This paper proposes a Hybrid approach of Modified Cuckoo search algorithm (MCSA) with Fuzzy logic for load frequency control in an interconnected thermal power system. Generation rate constraint (GRC) is considered as nonlinearities. A widely used linear model of the reheat thermal power system equipped with PI controller is considered for the design and analysis. An Integral time weighted absolute error (ITAE) is evaluated as objective function . Based the on objective function value the optimal scaling factors of membership functions are selected. MCSA is implemented for getting the optimal range of membership functions of the controller variables. Further robustness and stability analysis are also carried out by varying the load conditions and time constants of speed governor, turbine , power system and tie-line power in the range of -50% to +50%. To demonstrate the effectiveness of the proposed MCSA Fuzzy controller , a comparative study has been made with the Conventional PI controller and Type 2 Fuzzy controller.

Keywords — Load frequency control, Fuzzy logic controller, Cuckoo search algorithm, PI controller, Optimization.

1. Introduction

A typical large-scale power system consists of many control areas interconnected together and power is exchanged between control areas through tie-lines by which they are connected. In such systems, frequent changes occur due to the imbalance between the electrical load and the power supplied by system connected generators. Thus a control system is essential to offset the effects of the random load changes and to keep the frequency and the voltage at the constant values [1]. The active power and frequency control is referred to as load frequency control (LFC), which is also responsible for supplying sufficient and reliable electric power with better quality [2]. The main objectives of Load Frequency Control are to keep the system frequency at the schedule value and regulate the generator units based primarily on area control error (ACE). A number of control strategies have been employed in the design of load frequency controllers. Most of the control techniques are based on conventional proportional integral (PI) controller [3,4] due to the simplicity, ease of implementation and nature of the control strategy. Conventional controllers are usually tuned based on pre specified operating conditions. In case of any change in the operating condition, the fixed gain controller cannot provide the assigned desirable performance immediately [5]. To provide optimum performance, the PI controller should continuously track the changes occurring in the power system.

To improve the performance of the power system under dynamic condition, a new robust load frequency control using fuzzy logic controller (FLC) has been developed [6-8]. The major drawback of the FLC design is the difficult choice of the membership function scaling factors. The tuning procedure in FLC depends on the experience and knowledge of the operator. It is generally achieved based on a classical trial–error procedure. If the complexity of power system increases, this tuning procedure becomes more complex and hard.

To overcome this, Genetic Algorithm (GA) based fuzzy logic controller for LFC in two area interconnected power system was proposed [9]. Unfortunately recent research has identified some deficiencies in the performance of GA [10]. It was found that, the parameters being optimized are highly correlated. Also, the premature convergence of GA results in degrades performance and reduces the search capability with revisiting the same solutions. To overcome the problem of sub-optimal convergence of GA, particle swarm optimization (PSO) algorithm has been proposed [11]. Moreover, the algorithm relieves from slow convergence in a refined search stage and weak local search ability this may lead to possible entrapment in local minimum solutions [12]. A new evolutionary algorithm called Bacteria Foraging Optimization Algorithm (BFOA) has been proposed for the optimal design of PI controller to LFC in a two area interconnected power system [13]. However, during the process of chemotaxis in BFOA, may lead to delay in reaching the global solution [14].

Recently, Cuckoo Search Algorithm (CSA) has been proposed by Yang and Deb [15]. This metaheuristic algorithm has been applied successfully to continuous nonlinear function and optimization problem [16]. Further it shows that [14, 17], CSA outperforms than PSO, BFOA and ABC algorithms in solving optimization problems. To improve the local, global search ability and convergence rate, an Improved Cuckoo Search algorithm (ICSA) based on the CSA framework in combination with variable values of abandon probability and step size has been proposed [18]. In this work, a Modified Cuckoo Search Algorithm(MCSA) with position updating operator is proposed to optimize the membership functions of the fuzzy logic PI controller. The proposed controller is implemented in a simulated model of two-area reheat thermal power system in the presence of Generation Rate Constraint (GRC). The dynamic performance of proposed controller is compared with the performance of conventional PI controller and Type-2 fuzzy controller. The simulation results shows that the proposed MCSA fuzzy controller provides the robust performance for a wide range of operating conditions.

2. System Description

The system under study is composed of two area reheat thermal power system as shown in Fig 1.

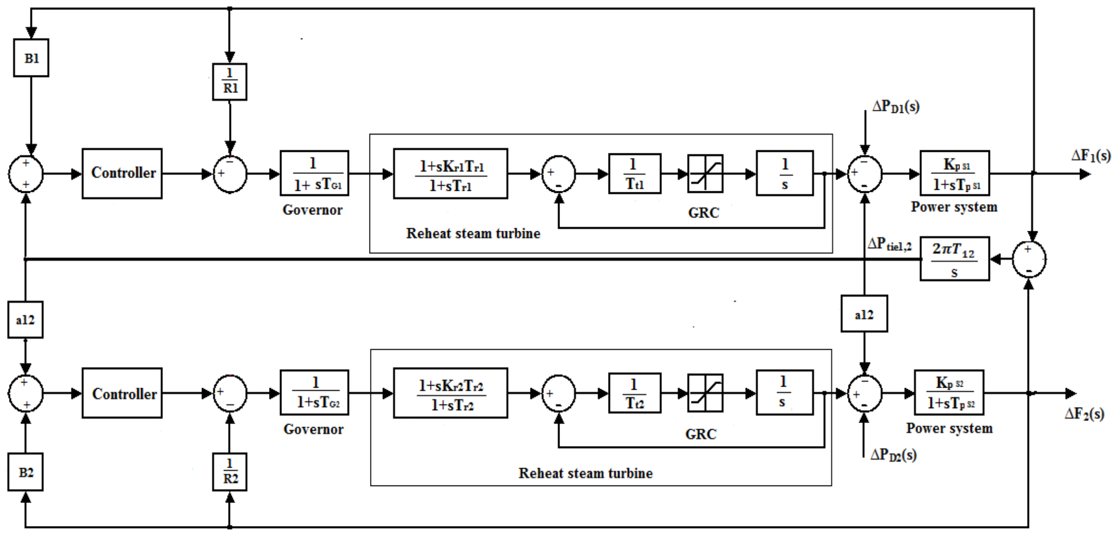

Fig 1. Two Are as Interconnected Reheat Thermal Power system

The applied GRC to non-reheat and reheat thermal turbines are 10% and 3% pu MW/min, respectively [19]. The generation rate constraints for both areas are taken into account by adding limiters to the turbines as shown in Fig. 1. In practical systems, there is a maximum limit to the rate of change in generative power of a steam plant. It has been shown that the dynamic responses of a system in the presence of nonlinearities have larger overshoots and longer settling times, compared with a system which does not consider nonlinearities [20, 21]. A generation-rate limitation of 0.1 p.u. per minute is considered here and is given by,

$$\Delta\dot{P}_g \leq 0.1\, p.u.min = 0.0017 p.u./sec$$

Reduction of the area control error (ACE) to zero is the main objective of the load frequency controller in power system. ACE is the linear combination of net tie-line power flow error ($\Delta Ptie_{i,j}$) and frequency error (ΔF_i) and represented as [2]:

$$ACE_i = \sum_{j=1}^{n} \Delta P_{tie\, i.j} + B_i \Delta F_i \tag{1}$$

where Bi is frequency bias coefficient, $\Delta P_{tie\ i,j}$ is tie-line power interchange error and ΔFi is the frequency error component.

The actual power exchanged in tie line is given by,

$$\Delta P_{tieij}^{actual} = \frac{2\pi T_{ij}}{s}\left(\Delta F_i - \Delta F_j\right) \tag{2}$$

The tie line power interchange error is given by,

$$\Delta P_{tieij}^{error} = \Delta P_{tieij}^{scheduled} - \Delta P_{tieij}^{actual} \tag{3}$$

A performance index can be defined by the Integral Time weighted Absolute Error (ITAE) of the frequency deviation of both areas and tie line power flow. The objective function J is set to be ,

$$J\,(K_{pi}, K_{Ii}) = \int t\,(\Delta F_1| + |\Delta F_2| + |\Delta P_{tie1,2}|\,)\,dt \tag{4}$$

3. Conventional and Fuzzy PI Controller

In this study, the conventional PI controller parameters are tuned by the well-known Ziegler-Nichols method. The fixed gain values are, $K_{p1} = K_{p2} = 8.723$ and $K_{i1} = K_{i2} = 1.575$.

The structure of the Fuzzy PI controller is shown in Fig.2

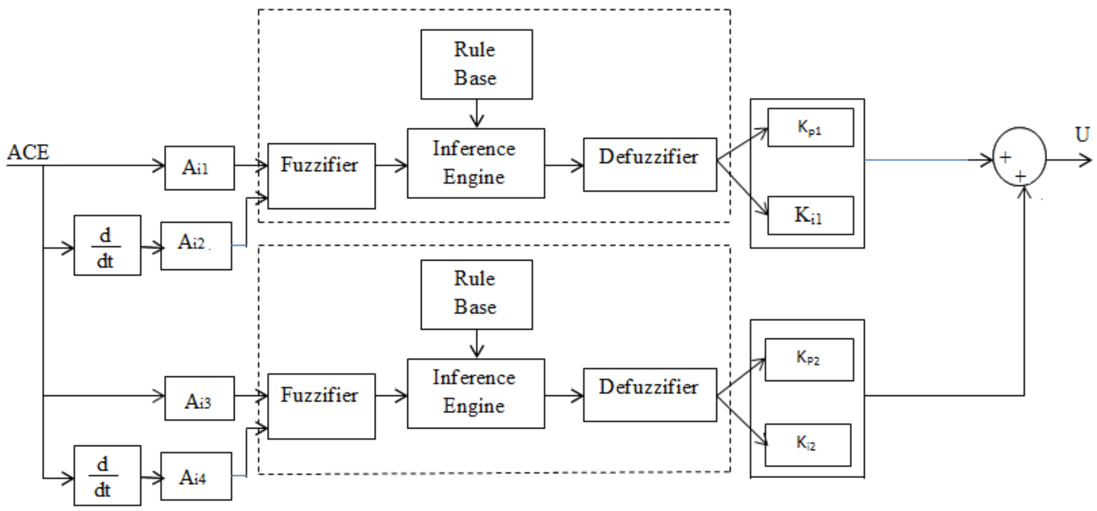

Fig. 2 Fuzzy PI Controller

The fuzzy logic controller has fuzzification block, the inference mechanism, fuzzy rule base and defuzzification block. In fuzzification block, the crisp input information (ACE and ΔACE) from the control area is converted into fuzzy values using the membership functions stored in the fuzzy knowledge base [22]. The inference mechanism determines how the fuzzy logic operations are performed, and together with the knowledge base determines the output of each fuzzy rule [23,24]. Knowledge base consists of two more blocks such as Database and Rule base. The Database consists of the membership functions of input and output variables described by linguistic values. The linguistic values employed in this work are denoted as N, Z, and P which stand for Negative, Zero and Positive respectively. The rule base includes all the rules which are formed by expert's knowledge.

In PI control strategy, the control output U_i of area 'i' is given by,

$$U_i = K_{Pi}\, ACEi(t) + K_{ii} \int ACEi\,(t)\, dt \quad (5)$$

Each fuzzy rule i in the fuzzy controller is of the form,

IF ACE_i (t) is A_{i1} and ΔACE_i (t) is A_{i2}
Then K_{p1} is u_i and K_{i1} is v_i
IF ACE_i (t) is A_{i3} and ΔACE_i (t) is A_{i4}
Then K_{p2} is p_i and K_{i2} is q_i

Where A_{ij} is a membership function, u_i, v_i, p_i and q_i are the singleton values. In this study, a Gaussian membership function is used whose value is given as [25]:

$$A_{ij}\,(x) = exp\left[-\frac{1}{2}\left(\frac{x_i - c_{ij}}{\sigma_{ij}}\right)^2\right] \quad (6)$$

Where x_i is the i^{th} input variable, c_{ij} is the centre and σ_{ij} width of the Gaussian fuzzy set A_{ij}. The firing strength of each fuzzy rule is calculated by fuzzy AND operation, which is given below:

$$\mu_i = \prod_{j=1}^{4} A_{ij} \quad (7)$$

The final output K_{P1} and K_{I1} are calculated by,

$$K_{P1} = \frac{\sum_{i=1}^{r} u_i \mu_i}{\sum_{i=1}^{r} \mu_i}\ ;\ K_{I1} = \frac{\sum_{i=1}^{r} v_i \mu_i}{\sum_{i=1}^{r} \mu_i} \quad (8)$$

where r is the total number of rules.

4. Cuckoo Search Algorithm

Cuckoo Search Algorithm (CSA), is a population based stochastic global search algorithm that is developed by Yang and Deb [15]. CSA is based on the brood parasite behavior of cuckoo kids and the Lévy flight behavior of some birds and fruit flies. Cuckoos are the fascinating birds, for their melodies voice and their aggressive reproduction strategy. Some species lay their eggs in communal nests, though they may remove other eggs to increase the hatching probability of their own eggs [16]. Quite a number of species engage the obligate brood parasitism by laying their eggs in the nests of other host birds. If a host bird discovers the eggs are not of its, it will either throw these alien eggs away or simply abandons its nest and builds a new nest elsewhere. Some cuckoo species are often very specialized in the mimicry in colour and pattern of the eggs of a few chosen host species [17]. This reduces the probability of their eggs being abandoned and thus increases their productivity.

4.1 Lévy flights

In general, the foraging path of an animal is effectively a random walk because the next move is based on the current location and the transition probability to the next location. Which direction it chooses depends implicitly on a probability which can be modeled mathematically. For example, various studies have shown that the flight behavior of many animals and insects have demonstrated the typical characteristics of

Lévy flights [16]. Subsequently, such behaviour has been applied to the optimal search. The following rules are used in the Cuckoo search Algorithm:

(a) Each cuckoo lays one egg at a time, and dumps it in a randomly chosen nest.
(b) The best nest with high quality eggs (solutions) will carry over to the next generation.
(c) The number of available host nests is fixed, and the egg laid by a cuckoo is discovered by the host bird with a probability P_a. In this case, the host bird can either get rid of the egg, or simply abandon the nest and build completely a new nest.

The above mentioned three rules are implemented for search methodology in the following way [26]:

An egg represents a solution and is stored in a population. A population can have many solutions. A new solution is generated randomly and choose a randomly position.

- Evaluate the objective function with the current position to choose the best solution
- Based on the objective function value, the worse solutions are identified and may discard it by a fraction P_a of the n solutions and replace it by a new solution. The probability of discovery is related to the similarity of the new solution to the existing solution.
- The best solution is carried over to the next iteration.

The initial locations of the solutions are determined by the set of values randomly assigned to each decision variable as:

$$y_{i,j}^{(0)} = y_{j.\min} + (rand)(y_{j.\max} - y_{j.\min}) \tag{9}$$

where $y_{i,j}^{(0)}$ denotes the initial value of the j^{th} variable for the i^{th} solution; $y_{j.min}$ and $y_{j.max}$ are the minimum and the maximum allowable values for the jth variable; rand is a random number in the interval of [0, 1].

$$y_i^{(t+1)} = y^{(t)}_i + \mu \Theta Le'vy(\lambda) \tag{10}$$

where $\mu > 0$ is the step size which should be related to the scales of the problem of interests. The product Θ means entry-wise multiplications. New solutions are generated by Lévy flight using (10), around the current best solutions.A Lévy flight is a random walk in which the step-lengths (λ) are distributed according to the following probability distribution [15]:

$$Le'vy(\lambda) = t^{-\lambda} \; ; 1 \le \lambda \le 3 \tag{11}$$

By using Mantegna Algorithm, the step length is evaluated as follows [14]:

$$Le'vy(\lambda) = \frac{u}{|v|^{1/\lambda}} \tag{12}$$

where u and v are taken from normal distribution as: $u \sim N\ (0,\ \sigma_U^2)\ , v \sim N\ (0,\ \sigma_v^2)$

$$\sigma_u = \left(\frac{\Gamma(1+\lambda)\sin(\pi\lambda/2)}{\Gamma\left[\left(\frac{1+\lambda}{2}\right)\lambda^{2(\lambda-1)/2}\right]} \right)^{1/\lambda}, \quad \sigma_v = 1 \tag{13}$$

where Γ is the standard gamma function.

5. Modified Cuckoo Search Algorithm (MCSA)

The performance of CSA in finding the optimal solution, is mainly depends on the selection of solution variables, abandon fraction (P_a) and step size (μ). In traditional CSA, new solutions are generated without the application of weight factor. The search ability of CSA can be improved by the application of weight factor and generate new solutions. The traditional CSA uses fixed value of abandon fraction (P_a) and step size (μ). The main drawback of this fixed value is increases the number of iterations to find an optimal solution. If the value of P_a is small and the value of μ is large, the algorithm will take more number of iterations to reach the optimal solution. If the value of P_a is large and the value of μ is small, the speed of convergence is high but the obtained solution may not be the best solution [18]. To overcome the above mentioned drawback, the traditional CSA has been modified to improve the efficiency of the algorithm in the selection of the variables. In the proposed MCS algorithm, the following modifications are performed:

(i) Lévy flight integrating with the inertia weight (w) is implemented. This modified Lévy flight is used for the generation of new solutions ($y_i^{(t+1)}$) from the current solution ($y_i^{(t)}$). By this way the search ability of the algorithm can be improved.

The new solutions generated by the improved Levy flight is given by,

$$y_i^{(t+1)} = wy_i^{(t)} + \mu \Theta Le'vy(\lambda) \tag{14}$$

The larger value of w has the greater global search ability, whereas the smaller value of w has the greater local search ability. To improve the search ability, the value of w is linearly decreased from relatively large value (w_{max}) to a small value (w_{min}). So that as compared with a fixed value of w used in CSA, the proposed MCSA provides an improved performance. The inertia weight w is expressed as [27]:

$$w = w_{\max} - \left(\frac{w_{\max} - w_{\min}}{Iter_{\max}} \right) \times Iter \tag{15}$$

where w_{max} and w_{min} are the initial and final weight respectively. *Iter* is the current iteration number and $Iter_{max}$ is the maximum iteration number.

(ii) Fixed values of P_a and μ are replaced with variable values to improve the performance and speed of convergence.

The performance of the algorithm can further be improved with the reduced number of iterations and the fast convergence. This is achieved by the variable values of abandon fraction (P_a) and step size (μ). In this work, the values of P_a and μ are dynamically changed with the number of generations and are expressed as follows [18]:

$$P_a^t = P_a^{\max} - \frac{t}{N}\left(P_a^{\max} - P_a^{\min}\right); \;\; \mu_t = \mu_{\max}\exp(ct) \qquad (16)$$

where N – Maximum number of iterations; t - current iteration; c – random Numbers ;

The value of c is taken as follows:

$$c = \frac{1}{N}\ln\left[\frac{\mu_{\min}}{\mu_{\max}}\right] \qquad (17)$$

In MCS algorithm, the parameters values are adjusted in each generation, so that the better solutions can be achieved. The values of a P_a, μ and w are dynamically changed with the number of iterations and the changes are expressed by eqn.(15-17).

6. Hybrid MCSA Fuzzy logic Control

The main objective of hybrid MCSA fuzzy logic approach is to select optimal values of the boundaries of the membership functions of the proposed fuzzy logic controller. Before describing in detail the main issues of coding and initializations are to be discussed. Coding means the way of membership functions and other parameters are represented as host nests. Initialisation is the proper assignment of learning constants before entering the optimization process [28].

Coding :

The fuzzy network is designed by using the number of fuzzy rules employed. Suppose there are r rules, then the order of parameters coded as individuals (host nests) is of the form,

$|c_{11}||\sigma_{11}||c_{12}||\sigma_{12}||c_{13}||\sigma_{13}||c_{14}||\sigma_{14}|[u_1]|v_1||p_1||q_1|$- for rule 1

-
-
-

$|c_{r1}||\sigma_{r1}||c_{r2}||\sigma_{r2}||c_{r3}||\sigma_{r3}||c_{r4}||\sigma_{r4}|[u_r]|v_r||p_r||q_r|$ - for rule r (18)

The individuals are randomly assigned within its searching range. The searching range of input variables membership functions are given as,

ACE_i = [-1 1]; ΔACE_i= [-0.1 0.1] ; c_{ij} = [-1 1] ; σ_{ij} = [0.05 1]

The searching range of output variables membership functions are given as,

u_i = [-10 10] ; v_i = [-5 5] ; p_i = [-10 10] ; q_i = [-5 5];

Within the searching range the position and width of each fuzzy set are selected independently by the application of flexible partition.

Initialisation:

In hybrid MCSA fuzzy, the initial population size of n (individuals) in the form of (18) is generated randomly. Here each nest represents a set of solution corresponds to a fuzzy system consists of r rules are produced. For each nest, the initial values of c_{ij} and σ_{ij} are assigned randomly within their searching range. The specifications of variables applied in MCS Algorithm are mentioned in Table 1.

Table 1. Specifications of MCSA

Population size (n)	Iterations (N_i)	Abandon Fraction (P_a)		Step size (μ)		Inertia weight (w)	
50	100	P_a^{min}	P_a^{max}	μ_{min}	μ_{max}	w_{min}	w_{max}
		0.005	1	1	3	0.5	2

Implementation:
After initialization, the objective function as in (4) is evaluated for all the nest values. In each iteration, better nests are generated based on levy flight random walk step size after elimination of worst nests. Then, the algorithm verifies for convergence condition, if it does not meet the convergence the nest values (controller parameters) are updated based on (14) . The procedure is repeated until the convergence condition is met (100 iterations) and the solution which provides low objective function value (J) and faster settling time is considered as the optimal solution. When sudden load changes (disturbances) are taking place the optimal parameter values are also changed and the system provides better performance as compared to the fixed gain controller. The flow of these operations is also depicted in Fig 3.

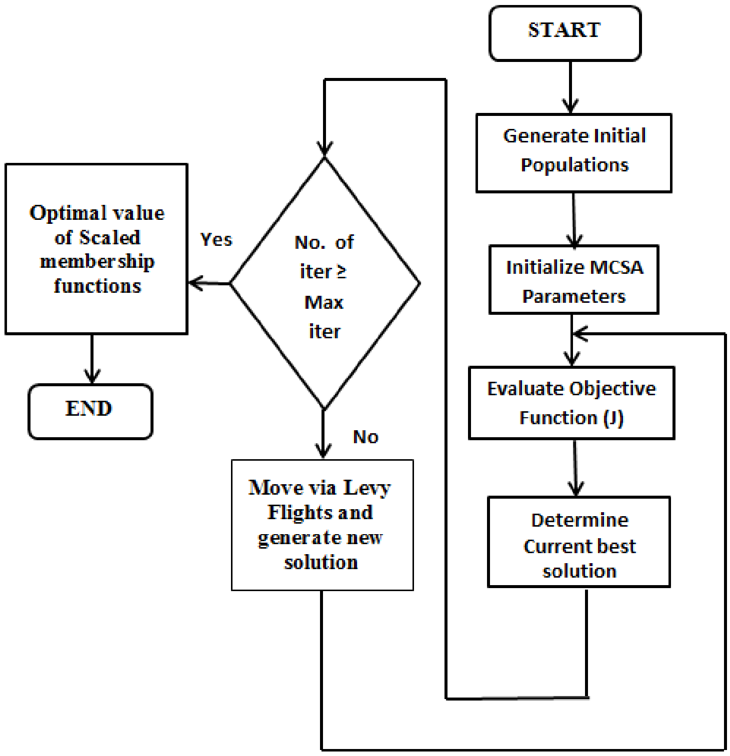

Fig 3. Flow chart of MCSA Fuzzy control

The optimal values of membership functions obtained using MCS algorithm based on the searching range are summarized in Table 2.

Table 2. Optimal values of Membership functions

A_{i1} A_{i2}	A_{i3} A_{i4}	u_i	v_i	p_i	q_i
0.4564 0.023	0.325 0.028	0.345	0.021	0.273	0.042

Based on the optimal values the membership function boundaries are selected. In this controller, three linguistic values such as negative (N), positive (P) and zero (Z) are used to tune the rules. There are nine rules are framed for the controller and are shown in Table 3.

Table 3. Fuzzy rules

Fuzzy Rules
IF ACE is N and ΔACE is N then K_{p1} is P and K_{I1} is N
IF ACE is Z and ΔACE is N then K_{p1} is N and K_{I1} is N
IF ACE is P and ΔACE is N then K_{p1} is N and K_{I1} is P
IF ACE is N and ΔACE is Z then K_{p1} is Z and K_{I1} is N
IF ACE is Z and ΔACE is Z then K_{p1} is N and K_{I1} is Z
IF ACE is P and ΔACE is Z then K_{p1} is P and K_{I1} is P
IF ACE is N and ΔACE is P then K_{p1} is N and K_{I1} is N
IF ACE is Z and ΔACE is P then K_{p1} is N and K_{I1} is P
IF ACE is P and ΔACE is P then K_{p1} is P and K_{I1} is N

7. Simulation Result:

The time domain simulation study of two area interconnected reheat thermal power systems is performed using Matlab/Simulink. The power system parameter values are given in Appendix. The nominal loading of each area is taken as 1500MW with the rated capacity of 2000 MW in each area and the participation factor (α_{11}) is chosen as 0.06746. By the implementation of MCS algorithm, the best final solution obtained after 100 iterations are taken as the optimized membership function boundaries of the proposed fuzzy controller. This optimized membership functions are implemented in the fuzzy controller, which controls the system under study. A Step load disturbance (SLD) of 10 % nominal loading is applied in either of the control area and the dynamic performance of the system has been analysed. Then the same SLD is considered in both areas simultaneously and the performance of the system are also analyzed. As the load disturbances have occurred in area1, at steady state, the power generated by generating units in both areas are in proportion to the area participation factors. Therefore, the power generation in thermal unit in control area increased by $\Delta Pg11_{ss} = \Delta Pg21_{ss} = \Delta PD_1 * \alpha_{11} = 0.1*0.6746 = 0.00674$ pu.MW.

7.1 Robustness Analysis

To demonstrate the robust performance of the proposed MCSA Fuzzy PI controller, three different load conditions are applied as follows:

Case I: Step load disturbance (SLD) in area 1 only

SLD of 10% increased nominal loading (ΔPD_1) is applied at t=0 in area 1. In this case ΔPD_2= 0. GRC for reheat turbines are 3% is simulated in this condition. The robust performance is verified by changing the system parameters by 40% of their nominal value. The frequency deviation of the first area ΔF_1, the frequency deviation of the second area ΔF_2 and inter-area tie line power flow of the system are shown in Figs. 4-6. The performance of the proposed MCSA Fuzzy controller is compared with the conventional PI controller, existing Type 2 Fuzzy controller [29] with respect to minimum damping ratios, settling time , undershoot and overshoot criteria. The system controlled by fixed gain controller takes more time to reach the steady state and also it has large overshoot, because of compromise made between the selections of controller parameters. It concludes that, the variable gain controller provides improved transient performance. Due to uncertainty membership functions, Type 2 FC also takes more time to reach the steady state and it also has large overshoot and undershoots. The optimized membership functions in the proposed controller, limiting the searching range of controller to improve the dynamic performance of the system when disturbances are occur. Due to perturbation applied in area 1, the response of the area 2 (Δf_2) have damping with smaller amplitude and settling time as compared to the response of the first area.

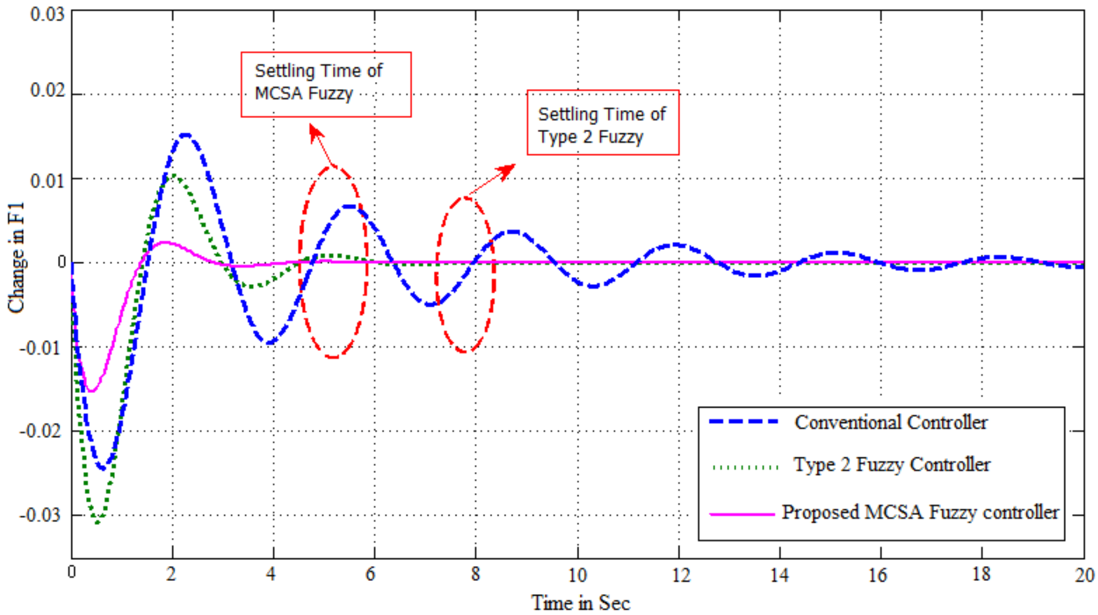

Fig 4. Changes in F2 when SLD applied in area 1

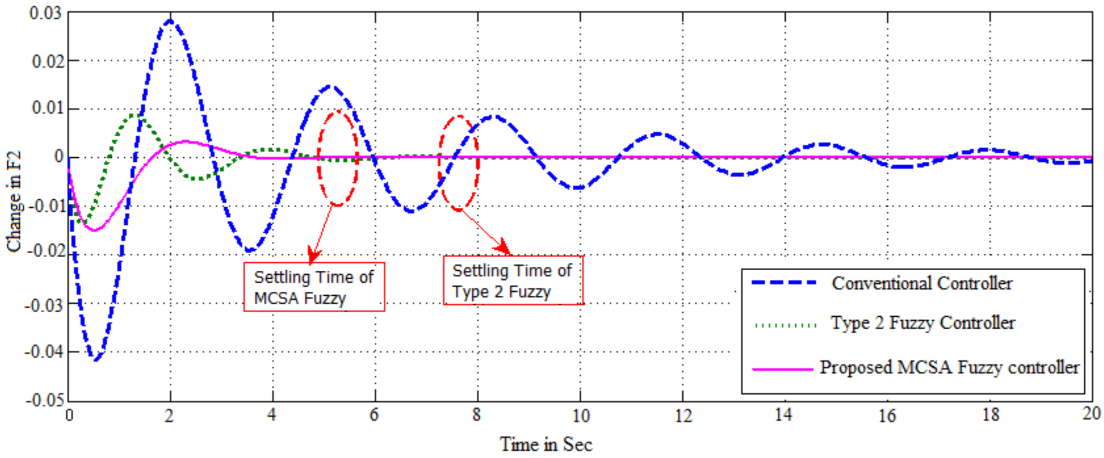

Fig 5. Changes in F1 when SLD applied in area 1

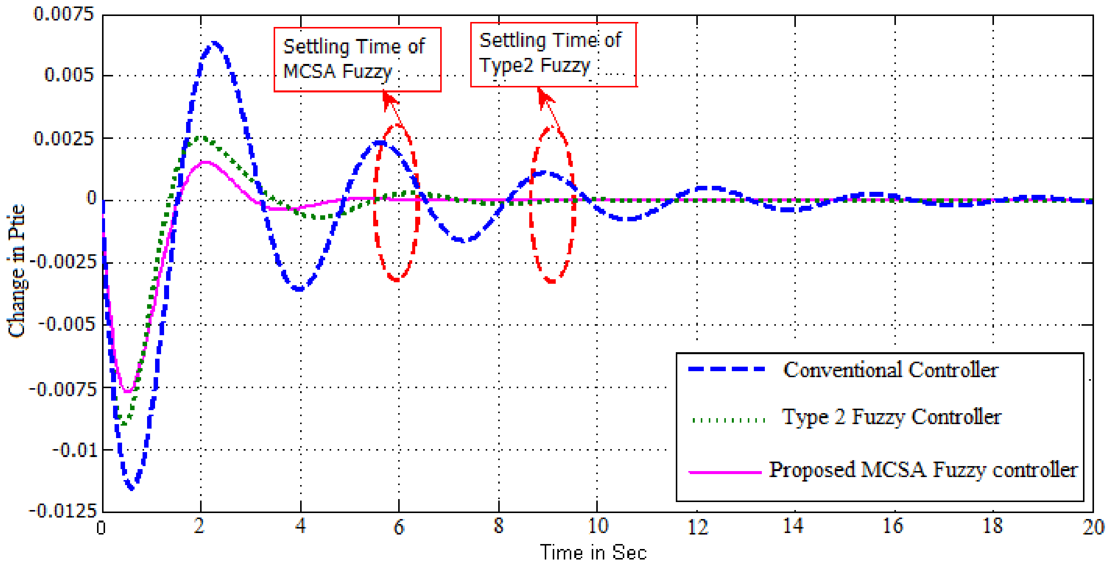

Fig 6. Changes in P_{tie} when SLD applied in area 1

Case II: Step load disturbance (SLD) in area 2 only

A SLD of 10% increased nominal loading (ΔPD_2) is applied at t=0 in area 2. In this case $\Delta PD_1 = 0$. The simulation parameters are the same as in case I. The frequency deviations in the first area ΔF_1, second area ΔF_2 and inter-area tie line power flow variations are shown in Figs.7-9. It is observed that, using proposed controller the frequency deviations, and inter area tie line power variations are quickly driven back to zero. The proposed controller provides improved dynamic performance in control and damping of frequency and tie line power variations when compared with conventional and Type 2 fuzzy controller.

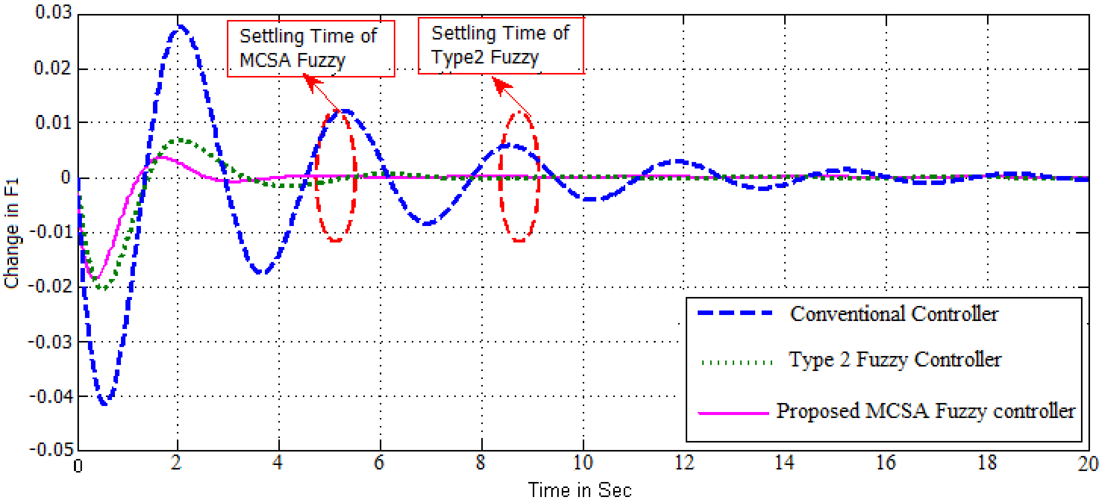

Fig 7. Changes in F1 when SLD applied in area 2 with GRC

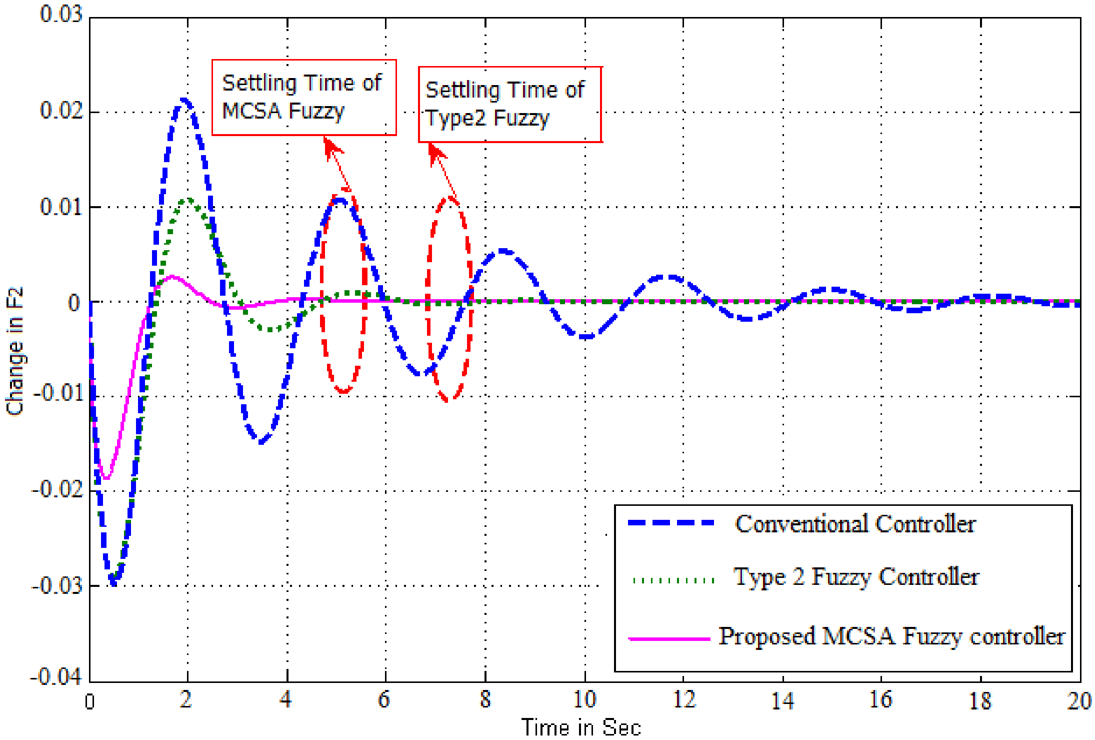

Fig 8. Changes in F2 when SLD applied in area 2 with GRC

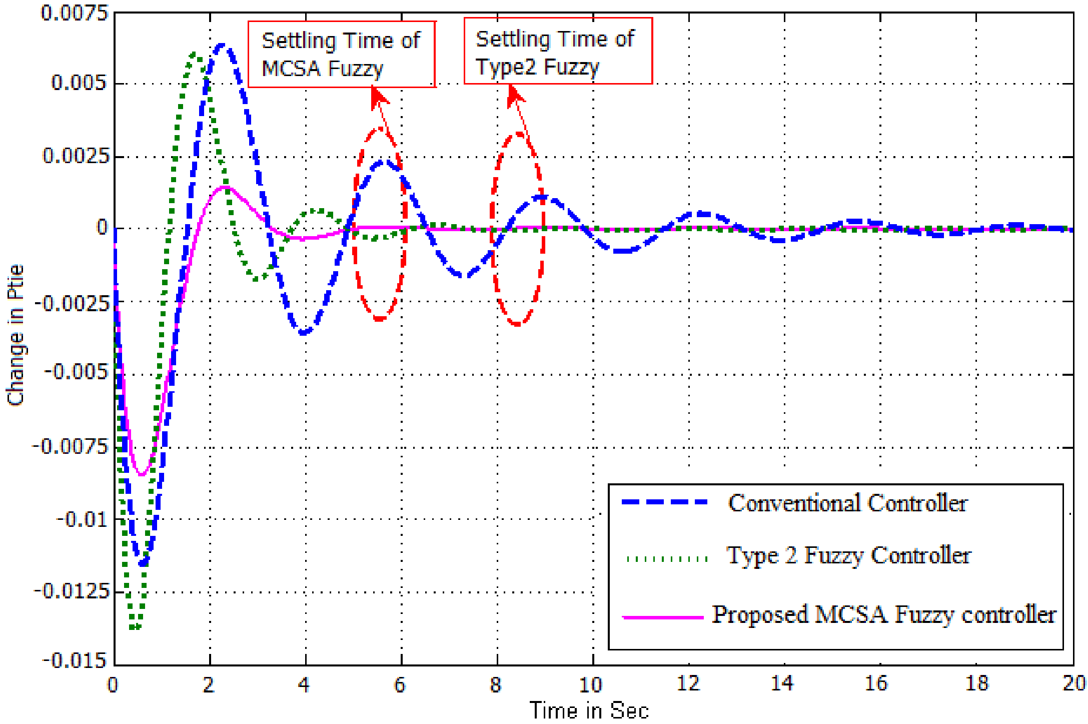

Fig 9. Changes in P_{tie} when SLD applied in area 2 with GRC

Case III: Step load disturbance (SLD) in both area
A step load disturbance of 10% nominal loading (ΔPD_1 & ΔPD_2) is applied at t=0 in area1 and 2 concurrently. The frequency deviations in the first area ΔF_1, second area ΔF_2 and inter-area tie line power flowvariations are as shown in Figs. 10-12. The system parameters are also changed by 40% from their nominal values. Also in this case because of the perturbation applied in both areas, the response of the area 1and 2 has damping with smaller amplitude and long settling time. In all the test conditions, the proposed MCSA Fuzzy controller provides better transient performance as compared to the conventional and Type2 Fuzzy controller . The robust performance of the above cases is shown numerically, when the system parameters are changed by 40% and the performance measures such as Overshoot, undershoot and settling time are listed in Table 4.

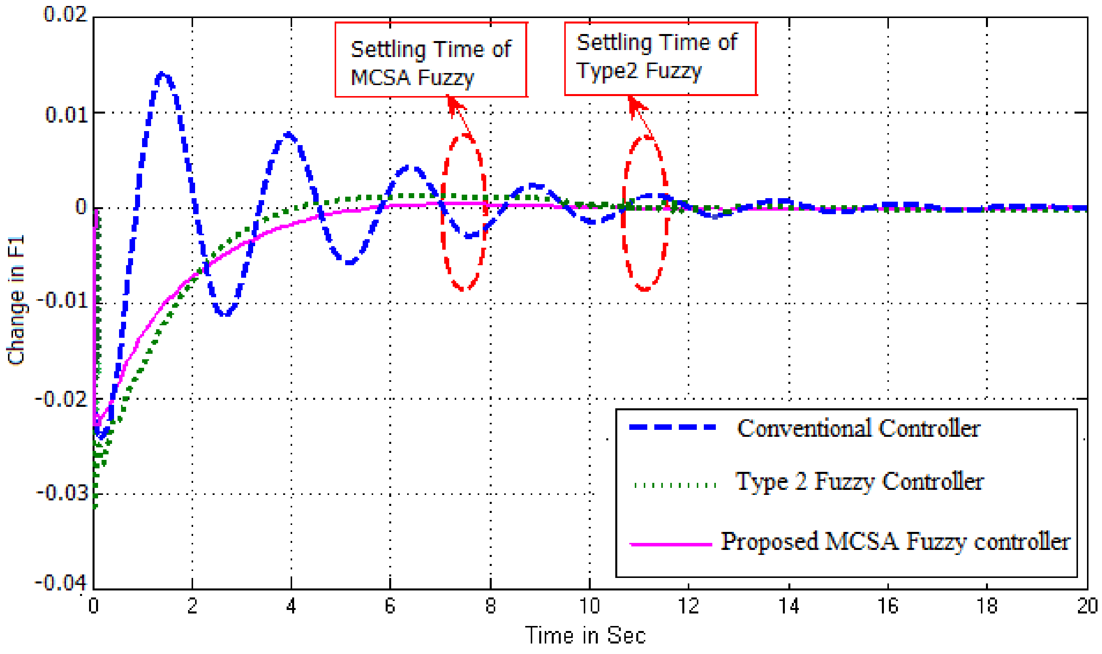

Fig 10. Changes in F1 when SLD applied in both area

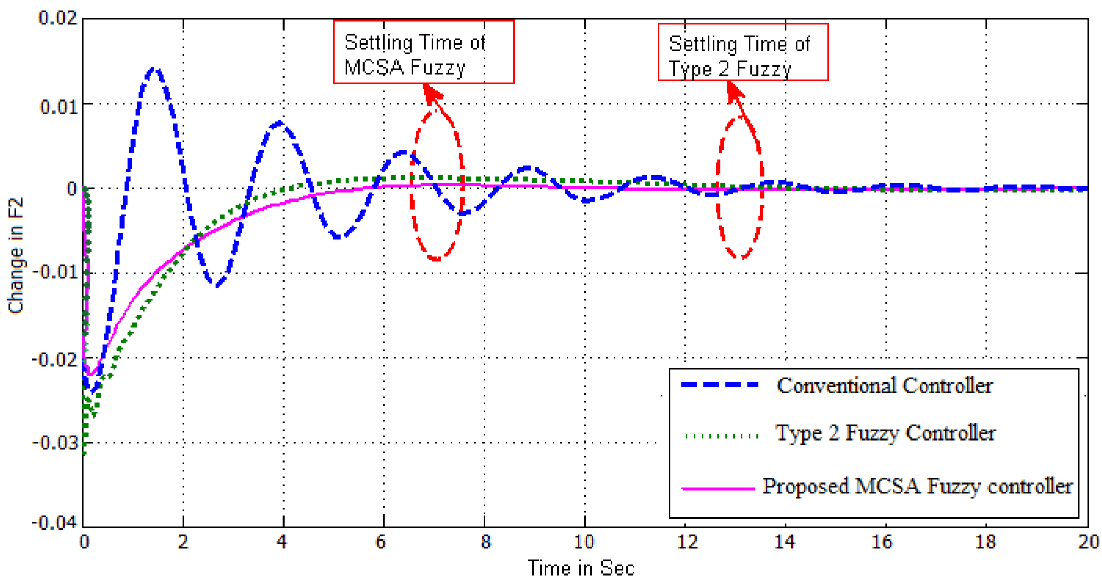

Fig 11. Changes in F2 when SLD applied in both area

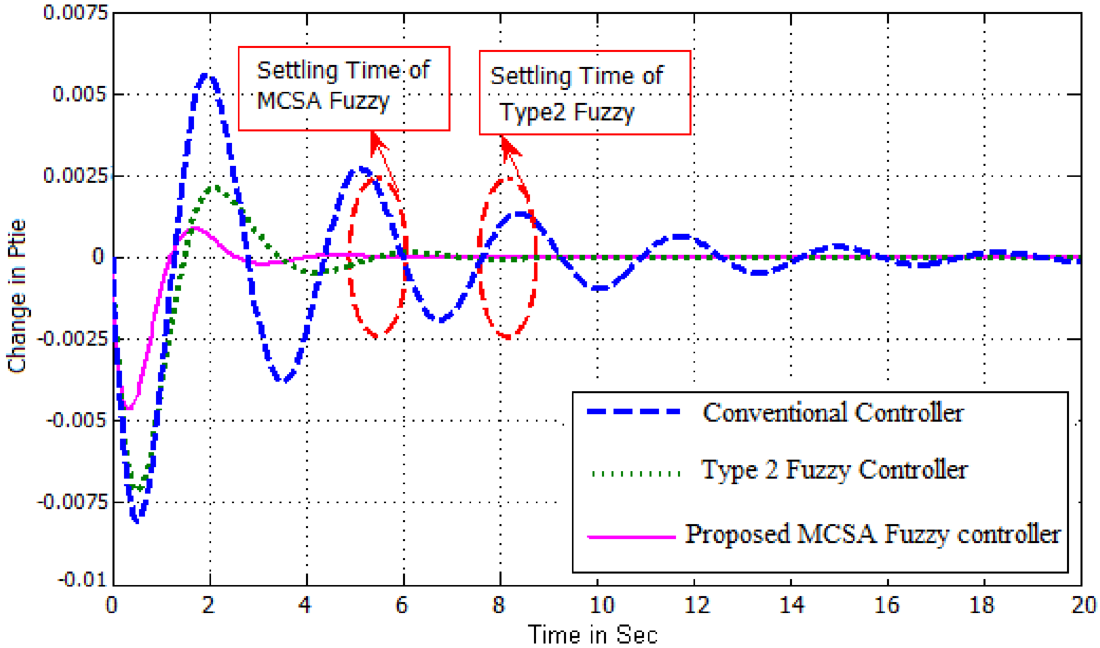

Fig 12. Changes in P_{tie} when SLD applied in both area

Table 4. Numerical Analysis

Input Parameters	Load Condition	Controller	ΔF_1			ΔF_2			ΔP_{tie}		
			Settling Time (sec)	Over Shoot (p.u)	Under Shoot (p.u)	Settling Time (sec)	Over Shoot (p.u)	Under Shoot (p.u)	Settling Time (sec)	Over Shoot (p.u)	Under Shoot (p.u)
T_{12} = 0.0866	Nominal Load	Conventional	28	0.012	-0.015	28	0.008	-0.025	26	0.005	-0.012
Bi = 0.545		Type 2 Fuzzy	7	0.006	-0.002	7.3	0.008	-0.001	6.8	0.003	-0.006
Ri = 2.4		MCSA Fuzzy	4	0.002	-0.001	4.1	0.001	-0.005	4.2	0.001	-0.003
Case I											
T_{12} = 0.1039	10% load Increased in Area 1	Conventional	34	0.017	-0.025	34	0.01	-0.031	35	0.006	-0.012
Bi = 0.654		Type 2 Fuzzy	8	0.011	-0.032	7.6	0.01	-0.012	8.5	0.003	-0.008
Ri = 2.88		MCSA Fuzzy	4.4	0.003	-0.015	4.4	0.003	-0.014	4.6	0.002	-0.007
Case II											
T_{12} = 0.1039	10% load Increased in Area 2	Conventional	32	0.028	-0.04	34	0.022	-0.03	34	0.006	-0.012
Bi = 0.654		Type 2 Fuzzy	8.5	0.008	-0.02	7	0.01	-0.041	8	0.006	-0.003
Ri = 2.88		MCSA Fuzzy	4.6	0.004	-0.018	4.8	0.004	-0.018	5	0.001	-0.008
Case III											
T_{12} = 0.1212	10% load Increased in both areas	Conventional	36	0.015	-0.032	38	0.015	-0.025	36	0.005	-0.007
Bi = 0.763		Type 2 Fuzzy	11	0.002	-0.004	13	0.002	-0.004	8	0.002	-0.008
Ri = 3.36		MCSA Fuzzy	7.1	0.000	-0.022	6.8	0.000	-0.021	5.2	0.001	-0.004

8. Conclusion

In this paper, an optimal design of fuzzy controller has been proposed for load frequency control in a two area interconnected reheat thermal power system. A Modified Cuckoo Search Algorithm is implemented to obtain the optimal membership functions of the fuzzy controller. The results obtained from the simulation study shows that , the proposed algorithm achieves better dynamic performance even in the presence of GRC. It is observed that the proposed controller is quite robust for a wide range of the system parameters and operating load conditions from their nominal values. To ensure the effective performance of the proposed approach, a comparative study has also been made among the Conventional , Type 2 fuzzy and the proposed MCSA Fuzzy controllers. The obtained simulation results demonstrate the efficiency of the proposed design approach in terms of improved dynamic performance and robustness of the system under disturbance conditions.

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Appendix

Nominal parameters of the two area thermal power systems are as follows:
P_r = 2000 MW (rating), P_L = 1000 MW (nominal loading) ; f = 60 Hz ; B1 = B2 = 0.425 pu MW/Hz ; R1 = R2 = 2.4 Hz/pu; $T_{G1} = T_{G2}$ = 0.08 s ; $T_{T1} = T_{T2}$ = 0.3 s ; $K_{PS1} = K_{PS2}$ = 120 Hz/pu MW ; $T_{PS1} = T_{PS2}$ = 20 s ; T12 = 0.545 pu ; a12 = −1.

Nomenclature

T_{PS1}, T_{PS2}	-	Generator time constants
K_{PS1}, K_{PS2}	-	Generator gains
T_{Gi}	-	Thermal unit governor time constant
T_{ri}, T_{ti}	–	Thermal unit reheat time constant
K_{ri}	-	Reheater gain
R_i	-	Governor speed regulation of the units of two-areas (i = 1,2)
P_{r1}, P_{r2}	-	Rated area capacities (a12 = P_{r1}/P_{r2})
T_{12}	-	Synchronizing coefficient
B_1, B_2	-	Frequency bias coefficients of two-areas respectively
K_{Pi}, K_{Ii}	-	Proportional and Integral gains of PI Controller