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Research paper

Application of Hybrid Modified Differential Evolution and Pattern Search Optimization Techniques for Automatic Generation Control of Power System

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Abstract

A hybrid Modified Differential Evolution (MDE) and Pattern Search (hybrid MDE-PS) method is suggested in this paper for Automatic Generation Control (AGC) of two-area diverse source power system. The thermal, hydro and gas power plants are considered for each area of the power system. DE is applied with different strategies to tune the gains of the integral controller using an ITAE criteria. After that, variation in DE technique is suggested for the best strategy by altering two control parameters (step size and crossover probability) with an objective of attaining superior performance. Subsequently, PS technique is applied to fine tuning of the ultimate solution contributed by MDE. Additionally, various controller arrangement and modified objective function are proposed and the optimal controller parameters are obtained with suggested hybrid technique. Furthermore, variation in system parameters and loading conditions is being carried out for sensitivity analysis. From the result of sensitivity analysis, the robustness of the proposed scheme is established. Finally, suggested scheme has been expanded to a more practical system with the nonlinearities.

Keywords: *Automatic Generation Control (AGC); Differential Evolution (DE) algorithm; Governor Dead Band(GDB); Generation Rate Constraint (GRC); Pattern Search (PS).*

1. Introduction

The key role of AGC is to maintain the steady frequency with the control of tie-line power flows by keeping balance in real power. AGC in each area regulates the generator set point automatically for the equivalent load change by forcing the Area Control Error (ACE) to zero [1-3]. In real applications, the interconnected power system contains thermal, hydro, gas and nuclear power generation. But, nuclear generating units are planned as base load plants due to their high efficiency and gas generating units are considered as peak load plants which can meet variable power demand. Hence, for the study of AGC considering mixture of diverse source generating units in the control areas with appropriate participation factors is more realistic [4]. In the literature, diverse control structures have been suggested by investigators in AGC of power systems to achieve good performance. In [5], a critical literature review related to AGC problem and distinct control methods including various intelligent/soft computing techniques which are pertaining to the problem of AGC. Now days in the area of AGC, new optimization approach have been extensively exercised to optimize the gains of different controller. In [6, 7], the authors were considered the several AGC based conventional controllers in an interconnected power system. An optimal control approach for AGC has been presented in [8]. In [9], the authors have studied the PID parameters which were tuned by Imperialist Competitive Algorithm (ICA) in an interconnected power system. Some novel technique/control approaches such as Firefly Algorithm (FA) tuned PI [10, 11], Flower Pollination Algorithm (FPA) tuned PID [12], Grey Wolf Optimization (GWO) tuned classical controller with PI/PID structure [13], hybrid FA Pattern Search (hFA-PS) tuned PI/PID [14], hybrid Stochastic Fractal Search and Local Unimodal Sampling (hSFS-LUS) based multistage PDF plus (1 + PI) [15] have been recently suggested for AGC of various types of power systems. It is evident from the literature review that, there is scope to work on AGC by investigating new controllers and optimization techniques. A classical PID controller and its modifications are always the industry's preference due to their simplicity in structure, lesser user-skill desires, nominal development effort and low cost.

The effectiveness of AGC depends on artificial intelligence techniques and objective function as observed from literature. DE is a population oriented algorithm which maintains the balance in the design domain between the exploration & exploitation stages of algorithm [16]. The techniques like GA and Expert Systems (ES), perturbation follows in harmony with a random quantity whereas in the case of DE, the population will be changed in accordance with weighted differences between solution vectors [17]. The success of DE critically depends on properly selection of trial vector generation strategies and their allied control parameter values namely the step size (F), cross over probability (CR), number of population (NP) and generations (G) [18]. So, it is essential to decide appropriate values of the control parameters at varied steps of evolution/search process. Also, a more relevant approach can be incorporate adaptively to suit the current problem [19, 20]. For better performance of any meta-heuristic technique it is necessary to keep an equilibrium among exploitation and exploration throughout the process. Global optimization technique DE if used alone, may provide an optimal/near optimal solution. Whereas, Pattern Search (PS) is a local optimizing technique and is suitable to search the solution in local area. Hence, PS should not be applied alone for global optimization [21, 22]. Keeping these points in view, there is an inspiration for DE and PS hybridization.

The new contributions of the current work are:

(i)A maiden approach has been made for the AGC with a hybrid Pattern Search (PS) and Modified Differential Evolution (MDE) technique.

(ii)Primarily, integral controllers have weighed for each unit and in order to minimize an ITAE criterion various strategies of DE are exercised.

(iii)After that alterations in the algorithm are offered by varying F and CR throughout the run for the greatest approach.

(iv)In addition to that in the proposed MDE algorithm, PS is employed to fine tune the controller gains. MDE and PS have complementary benefits, and it can result a quicker and stronger method by hybridizing the two algorithms.

(v)To show the effectiveness of the tuned controller parameters, variation in nominal values of system parameters, operating load condition is carried out to achieve sensitivity analysis.

2. Material and Methods

2.1. System under Study

Firstly, two-area with six-unit power system is taken as in Fig.1. As per the participation factor the load is distributed among the units. In [4] the system data's are taken and also provided in Appendix. Regulation parameters R_1, R_2 and R_3 shown in Fig. 1 denotes for thermal, hydro and gas unit respectively. The control outputs are represented as U_T for thermal, U_H for hydro and U_G for gas units. The participation factors are represented as K_T for thermal, K_H for hydro and K_G for gas units. T_{SG}, T_T represents time constant of speed governor for thermal units and reheat steam turbine in second respectively. T_W represents penstock base starting time of water in sec. T_{RS} represents reset time for speed governor, T_{RH} represents time constant for governor droop, T_{GH} represents time constant for main servo of speed governor of hydro turbine in sec respectively. X_C represents lead-time constants and Y_C represents lag-time constants of speed governor for gas turbine in sec respectively. c_g represents gas turbine and b_g represents valve positioned based gas turbine constant. T_F represents time constant of fuel and T_{CR} represents time delay of combustion reaction in sec of gas turbine.

T_{CD} represents time constant of discharge volume for compressor based gas turbine in sec. K_{PS} represents gain of power system in Hz/p.u.MW. T_{PS} represents time constant of power system in sec. Δ_F, Δ_{PD} are the variation in frequency and load respectively.

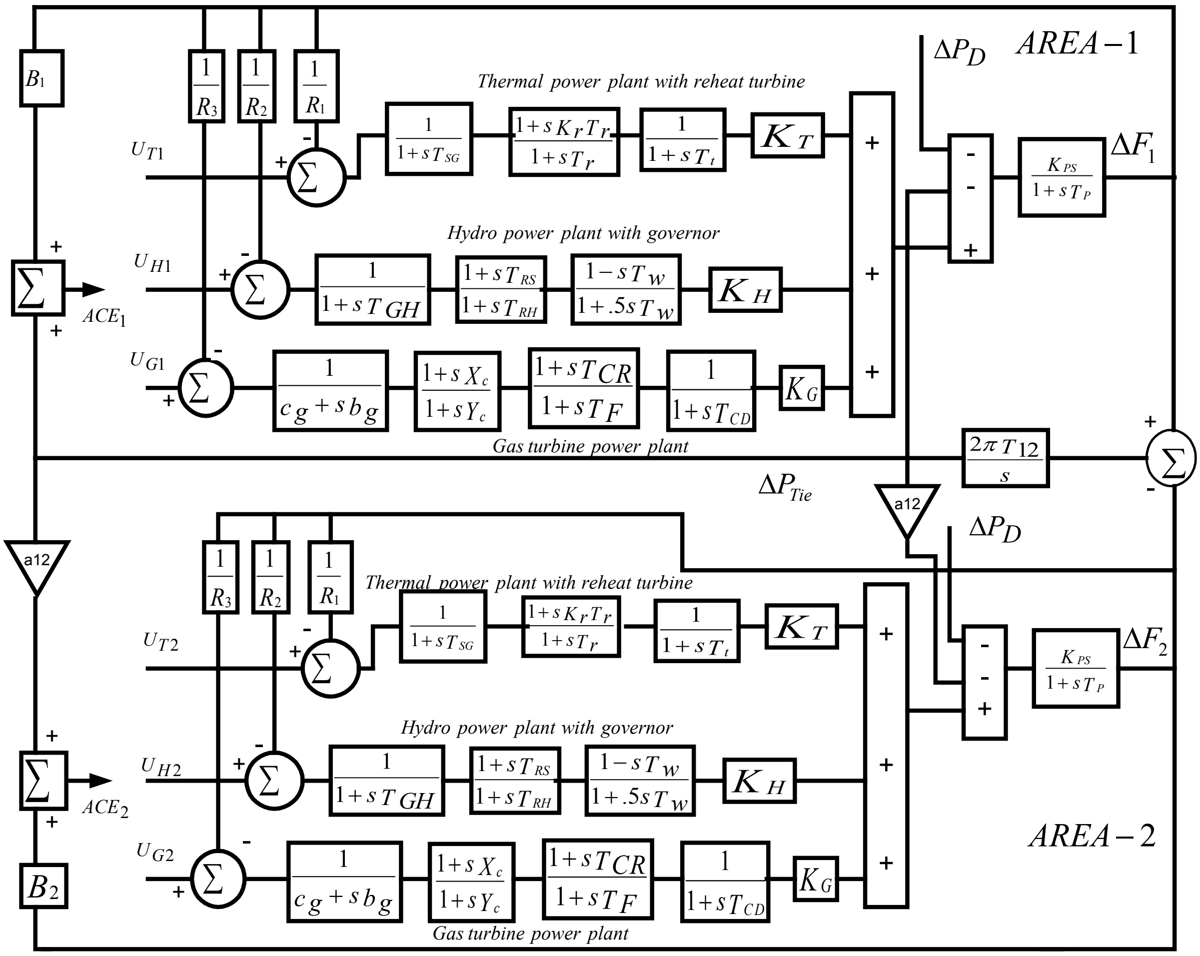

Fig. 1: Two-area with diverse source transfer function model [4].

2.2. Control Structure

Classical PID controller is well known and most accepted feedback controllers in industrial applications as its robustness and easy to design, economical, and most effective for linear systems. The proportional, integral and derivatives are the gains of the PID controller. The controller with only proportional action has the ability to reduce rise time, but steady state error cannot be removed. By using integral action this steady state error can be eliminated but the transient response of the system becomes poorer. This transient response can be improved by using derivative action and it also reduces overshoot and stability of the system. Predominantly, Proportional Integral (PI) controllers are mostly preferred controller in industries. But, when fast response is not required the PI controller is preferred. If large communication delays and noise are present in the system, it is required to use fast response PID controllers.

2.3. Objective Function

To employ optimization technique for controller design, an objective function is to be selected. In AGC problem, the parameters to be considered for objective function calculations are change in frequency deviation and tie-line power. In addition, it is also required to consider output specifications such as peak overshoot, settling time, rise time and steady-state error. In [9], the authors have reported that ITAE is better when compared to the others options. Two objective functions are considered in this work as given below:

$$J_1 = ITAE = \int_0^{t_{sim}} \left(|\Delta F_1| + |\Delta F_2| + |\Delta P_{Tie}|\right) \cdot t \cdot dt \tag{1}$$

$$J_2 = \int_0^{t_{sim}} \left[\left(\omega_1 \frac{d\Delta F_1}{dt}\right)^2 + \left(\omega_2 \frac{d\Delta F_2}{dt}\right)^2 + \left(\omega_3 \frac{d\Delta P_{Tie}}{dt}\right)^2 \right] \cdot t \cdot dt + \int_0^{t_{sim}} w_4 \left[|\Delta F_1| + |\Delta F_2| + |\Delta P_{Tie}|\right] \cdot t \cdot dt + \omega_5 \cdot \frac{1}{\min\left(\sum_{i=1}^{n} (1-\zeta_i)\right)} + \omega_6 (ST) + \omega_7 (OS) \tag{2}$$

Where, $\Delta F_1$and ΔF_2 are the change in frequencies of area-1 and 2 respectively, ΔP_{Tie} is the tie-line power deviation. t_{sim} is the time range of simulation, ζ_i is the damping ratio and n is the total number of the dominant eigen values; *ST* and OS is the sum of the settling times and peak overshoots of frequency and tie-line power deviations respectively; ω_1 to ω_3 are weighting factors of first term in the objective functions which are searched by the proposed optimization technique; ω_4 to ω_7 are the weighting factors which are incorporated in the proposed objective function to formulate each factor shows their impact during the optimization process. Appropriate weighting factors are being multiplied to the right hand side of individual terms of equation (2) which helps to make each term in the objective function competitive enough during the optimization method. A few number of trial runs are to be executed to finalize the weights and during this process the following weights are chosen: I controller: ω_4=0.0457, ω_5=0.0269, ω_6=0.008 and ω_7=3.027; PI controller: ω_4= 0.0419, ω_5=0.0397, ω_6=0.0064 and ω_7=2.9310; PIDF controller: ω_4= 0.006, ω_5=0.0123, ω_6=0.0019 and ω_7=0.3589.

3. Differential Evolution (DE) Algorithm

Differential Evolution (DE) algorithm is a population based stochastic algorithm developed by Storn and Price [16]. The basic purpose behind the development of this technique was to tune the actual parameters as well as actual valued functions without using its gradient. The technique keeps a set of agents from the population and is updated over about simple formulae to form fresh agents. In a D-dimensional search space situation initial a fixed set of vectors are prepared in an arbitrary approach from a population of prospective candidate solutions. Later they are developed over time for exploring the search space and for localizing the least of the objective function. Throughout each generation, a population of *NP* solution vectors is randomly selected from the current population within the parameter bounds. The population can be modified by applying the operators such as mutation, crossover. DE algorithm make use of old and new generations for the same population size. Throughout each generation, few vectors are arbitrarily chosen from the present population and by joining them some fresh vectors are created. The DE technique is described in more detail in [16].

4. Hybrid Pattern Search and Modified DE Approach

The conventional DE algorithm effectiveness has been greatly subjected to the control parameter values and the selection of strategies. The parameters of DE method are: *F*, *CR*, *NP* and *G*. In the literature [23- 29], several realistic rules for choosing strategies and the settings of related control parameter have been stated. From the literature survey, some contradictory conclusions are observed with regards to the rules for setting the control parameters and choosing the strategy without any proper justifications. In fact, most of the conclusions are confined to the particular problem, strategies and parameter values. Hence, it can be said that selecting a approach and settling the control parameter values is a problem-dependent assignment.

4.1. Modified Differential Evolution (MDE)

In this paper, a modified DE algorithm is suggested. Both *F* and *CR* are reduced linearly and exponentially at once in the range 1 to 0.02. The *F* and *CR* values are measured by the following relations:
For linearly decreasing:

$$F_G = F_{\max} - \left(\frac{F_{\max} - F_{\min}}{G_{\max}}\right) \cdot G \tag{3}$$

$$CR_G = CR_{\max} - \left(\frac{CR_{\max} - CR_{\min}}{G_{\max}}\right) \cdot G \tag{4}$$

For exponentially decreasing:

$$F_G = F_{\max} \cdot e^{(-K_1 G/G_{\max})} \tag{5}$$

$$CR_G = CR_{\max} \cdot e^{(-K_2 G/G_{\max})} \tag{6}$$

Where F_G and CR_G are the *F* and *CR* values at generation *G*, G_{max} is the maximum generation, F_{max} , F_{min} and CR_{max} , CR_{min} are the maximum and minimum values of *F* and *CR* respectively. The constants K_1 and K_2 values are so chosen that *F* and *CR* values are at their maximum limit at the first generation (*G*=0) and minimum values at the last generation ($G=G_{max}$). In search method, there is no surety that the result of technique is a global optimum. The PS method is applied to fine tune the best solution given by MDE method.

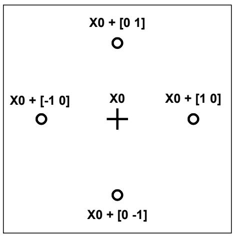

Fig. 2: Pattern Search mesh points and the pattern [14].

4.2. Pattern Search

The concept of PS method can be implemented easily. It has the capability to improve and adapt the global search and fine tune local search [30]. It provides set of points called mesh around the initial point. The starting point for the pattern search begins at the initial point X0, produced by the MDE algorithm. During the initial iteration, for the mesh size with a scalar = 1, the pattern vectors or direction vectors are constructed as (0 1), (1 0), (-1 0) and (0 -1). Then the direction vectors are added to the initial point X0 for computing the mesh points as X0 + (0 1), X0 + (1 0), X0 + (-1 0) and X0 + (0 -1) as shown in Fig. 2. The flow chart of proposed method is presented in Fig. 3.

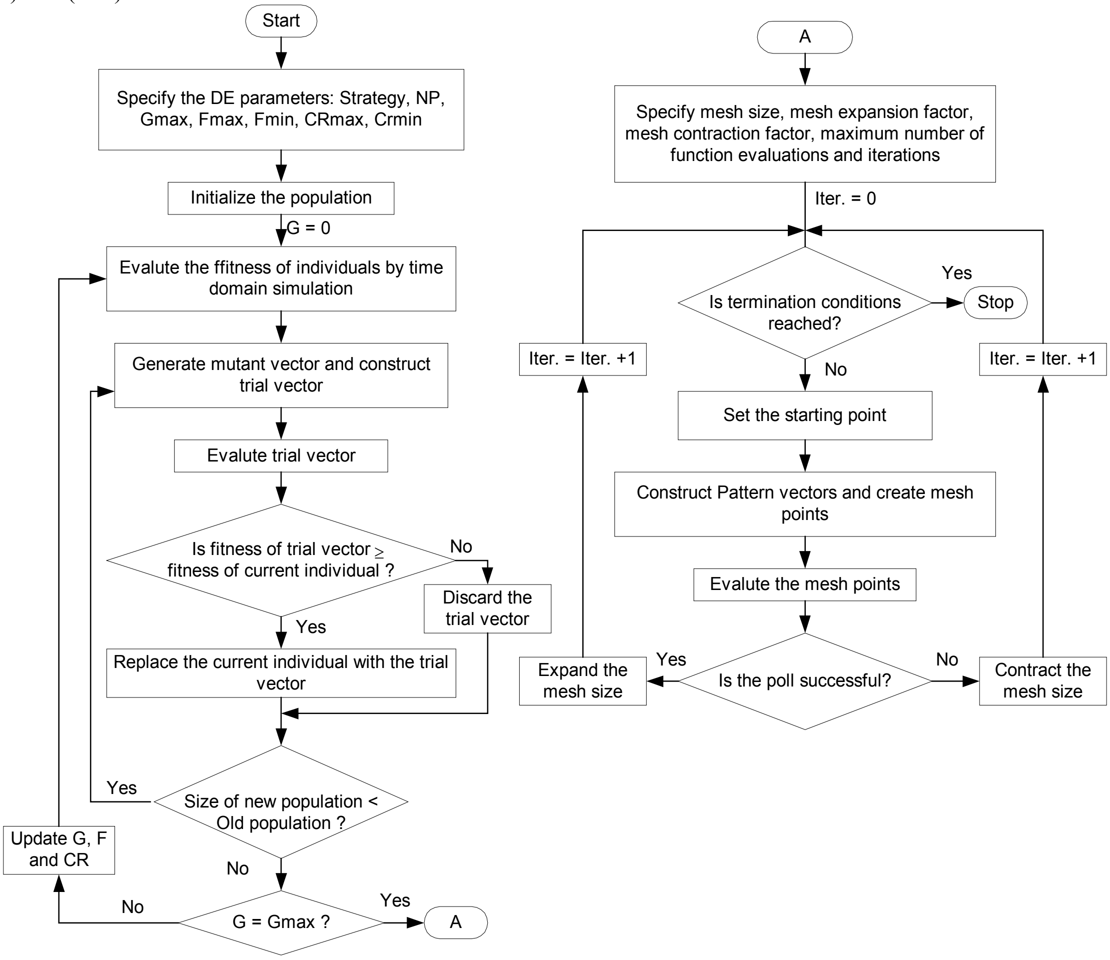

Fig. 3: Flow diagram of proposed hybrid Pattern Search and modified differential evolution.

5. Analysis of Results and Discussions

5.1. Selection of Parameter

The model is design & simulated in MATLAB with SIMULINK atmosphere for the test system (shown in Fig. 1). The model is simulated by selecting a 10% SLP in area-1. Since ITAE has been chosen as an objective function, ITAE value for the given test case is calculated and used in algorithm. For each unit, integral controllers are used initially and several strategies of DE are engaged to reduce the error value. To get the best final solution, the optimization was repeated 200 times for each strategy the corresponding values in terms of the minimum, average, maximum and standard deviation are provided in Table 1. It can be understood from Table 1 that, strategy 7 (DE/rand/1/bin) provides the lowest value for the system under study and therefore this strategy is selected for more study. In MDE, the values *F* and *CR* parameters are compressed exponentially and linearly as Equations (3)-(6). The reduction in control parameters throughout the path are finished in two methods: deviation of one control parameter at a stage and concurrently both the control parameters. The outcomes of above method over 200 self-governing runs are presented in Table 2. The utmost clear remark from this study is that the suggested technique offers the finest enactment when the control parameter *F* is reduced exponentially from 1.0 to 0.002 and *CR* is reduced exponentially from 1.0 to 0.02 throughout the course. Later choosing the structures for setting *F* and *CR*, other control parameters NP and G are fixed by changing *NP* from 10 to 50 and *G* from 30 to 200. The results of above parameter deviations have been presented in Table 3 above 200 self-governing runs. Table 3 shows that suitable setting of *NP* and *G* would take the slightest urgency (expect of very low NP values) when related to setting of control parameters F and CR. Note that rising *NP* and *G* beyond 30 will increase the solution precision somewhat at the rate of growing the calculation time widely. The enhancement in objective function is nearly insignificant for *NP* beyond 40 and *G* later 100. Based on the above groundwork, the following schemes/parameters are selected for the proposed modified DE algorithm:

i. Mutation Strategy: DE/rand/1/bin
ii. F: Exponentially decreasing from 1.0 to 0.002 during the run
iii. CR: Exponentially decreasing from 1.0 to 0.02 during the run
iv. Population size NP: 40
v. Generations G: 100

The value of ITAE by integral controllers for individually unit for a 10% SLP in area-1 is establish to be 22.6108. Then fine tuning of parameters obtained in MDE algorithm, PS is employed. The results of suggested hybrid pattern search and MDE technique over 200 self-governing runs are presented in Table 4. It can be observed from Table 4 that by using the PS method, the value of ITAE is furthermore declined to 20.4615 (i.e. 9.5% enhancement). Similarly improved results are detected in terms of average, maximum and standard deviation values with the suggested hybrid MDE method and pattern search correlated to MDE technique and original DE technique.

Table 1: Results, for different strategy.

Strategy No.	Technique	Min.	Ave.	Max.	St.dev.	Other parameters
1	DE/best/1/exp	25.4217	44.6658	94.9710	12.8616	
2	DE/rand/1/exp	24.3712	50.3757	115.3092	18.1304	
3	DE/rand-to-best/1/exp	27.0625	44.4481	193.4885	18.2868	NP=30
4	DE/best/2/exp	27.5135	48.6076	230.9829	24.8337	G=50
5	DE/rand/2/exp	27.6723	46.1793	134.0392	17.6093	F=0.8 and CR=0.8
6	DE/best/1/bin	24.9002	46.0168	234.3686	23.3847	
7	DE/rand/1/bin	24.3712	47.8115	115.3092	18.6680	
8	DE/rand-to-best/1/bin	25.8435	46.3481	134.0392	17.8059	
9	DE/best/2/bin	26.6795	47.0882	134.0392	17.9064	
10	DE/rand/2/bin	27.0305	47.1726	150.2218	19.0246	

Table 2: Results, for 200 independent runs, of improved DE (Changing F and CR concurrently).

other parameters: NP=30, G=50 and DE/rand/1/bin									
		Exponentially decreasing				Linearly decreasing			
Parameter		Min.	Ave.	Max.	St.dev.	Min.	Ave.	Max.	St.dev.
CR=1.0	F=1.0 to 0.5	25.9263	44.0744	132.0297	15.3907	27.0625	43.9659	193.4885	17.9700
	F=1.0 to 0.02	24.5130	46.6383	112.7949	16.9487	26.9179	42.1676	96.4428	12.4214
	F=1.0 to 0.002	27.3793	47.5456	118.6468	15.4655	25.4217	44.6507	94.9710	13.0183
F=1.0	CR=1.0 to 0.5	24.2880	45.8834	127.2439	17.6535	25.8435	46.7939	134.0392	19.0119
	CR =1.0 to 0.02	25.0954	44.9961	159.1546	18.0283	24.2854	50.3614	144.1009	20.7713
	CR =1.0 to 0.002	26.8302	46.2580	96.1835	15.6470	27.5134	47.9449	128.4529	18.9936
F=1.0 to 0.5	CR=1.0 to 0.5	25.0047	44.0382	87.2871	11.8550	24.2855	49.9867	144.1010	20.7542
	CR =1.0 to 0.02	24.6910	47.1451	123.2311	15.8038	24.1362	48.2515	230.9829	24.4006
	CR =1.0 to 0.002	25.4217	44.6658	94.9710	12.8616	24.9752	45.5653	115.9548	17.3819
F=1.0 to 0.02	CR=1.0 to 0.5	24.5923	49.2450	114.3351	18.4126	27.0625	44.4481	193.4885	18.2868
	CR =1.0 to 0.02	24.9149	44.1737	96.0948	14.5917	25.5157	42.0775	96.4428	12.4828
	CR =1.0 to 0.002	26.2135	44.3993	140.5974	16.8682	25.4217	44.6658	94.9710	12.8616
F=1.0 to 0.002	CR=1.0 to 0.5	24.0433	46.1528	106.3016	15.7117	27.3793	47.4941	118.6468	16.0434
	CR =1.0 to 0.02	22.8579	43.7934	136.4516	16.0742	24.2880	46.4329	127.2439	17.4351
	CR =1.0 to 0.002	26.6795	46.5344	134.0392	18.3038	26.6902	45.1180	159.1546	18.7581

Table 3: Results, for 200 independent runs of improved DE with exponentially decreasing F and CR.

Parameter	Min.	Ave.	Max.	St.dev.	Other parameters
NP=10	27.0305360686	47.6665511323	150.2218	19.1446	G=50
NP=20	24.9001548940	45.3679202910	234.3686	23.2586	DE/rand/1/bin
NP=30	22.8578929758	43.7934470946	136.4515	16.0741	F=1.0 to 0.002
NP=40	22.6705089317	42.7503567027	130.2084	15.1046	CR =1.0 to 0.02
NP=50	22.6701341052	42.1034470946	139.9630	16.7793	
G=30	22.6705089317	42.7503567027	130.2084	15.1046	NP=40
G=50	22.6430127324	42.1076519302	139.2398	17.3903	DE/rand/1/bin
G=100	22.6108360921	41.8603892137	137.0834	16.1492	F=1.0 to 0.002
G=150	22.61053095601	41.8210209743	159.3201	17.9097	CR =1.0 to 0.02
G=200	22.6101272154	41.8123032184	159.4947	18.2945	

Table 4: Results, for 200 independent runs of improved DE-PS.

Min.	Ave.	Max.	St.dev.	Algorithm parameters
20.4615	32.5850	90.5855	7.8972	Modified DE parameters: Strategy = DE/rand/1/bin, Population size NP=40, Generations G=100 Step size F=1.0 to 0.002 (exponentially decreasing) Cross over probability CR =1.0 to 0.02 (exponentially decreasing) PS parameters: Mesh size = 1, Mesh expansion factor = 2 Mesh contraction factor = 0.5 Maximum number of objective function evaluations =10 Maximum number of Iterations = 10

5.2. Performance Enhancement with Controller Arrangement

The results are obtained by considering a 10% SLP in area-1 and the integral controller gains are optimized with ITAE objective function. It is worthwhile to mention that, to have a better idea on proposed hybrid MDE-PS algorithm less effective integral controllers are considered initially. To improve the system performance, modified objective given in Equation 2 and PI & PID with derivative filter are selected. The proposed hybrid MDE-PS algorithm is applied with 10% SLP in area-1 & 200 independent runs are carried out. The optimal controller gains obtained by the suggested method and corresponding ITAE values along with the weights are presented in Table 5. The error values and settling times of frequency deviations, peak overshoot and minimum damping ratio for different objective functions and controllers are shown in Table 6. It is evident from Table 6 that, with similar objective function (J_1: ITAE) superior system performance is attained with PI compared to I controller and most excellent system performance is achieved with PIDF.

Table 5: Optimized parameters and weights with different controllers and objective functions.

Controller/Objective function parameter	I (J_1)	I (J_2)	PI (J_1)	PI (J_2)	PIDF (J_1)	PIDF (J_2)
K_{P1}	-	-	-1.9946	-1.9209	-1.6870	-1.8273
K_{P2}	-	-	1.1525	1.8572	-0.5917	0.2487
K_{P3}	-	-	-0.7506	-0.1185	-0.5867	-1.6007
K_{P4}	-	-	-1.0942	-1.5046	-1.5397	1.0107
K_{P5}	-	-	1.9751	1.8696	-0.0302	0.7682
K_{P6}	-	-	-1.7312	0.6268	-0.2669	-0.6240
K_{I1}	-0.2523	-0.2119	-1.8670	-0.8393	-1.0708	-0.8188
K_{I2}	-1.3966	-1.3596	-1.9863	1.0181	-1.2024	-1.0080
K_{I3}	-0.3621	-0.3005	-0.9895	-1.7675	-0.9715	-1.5728
K_{I4}	-0.0690	-0.0694	0.5277	-0.2888	-1.6241	-0.5251
K_{I5}	-0.0476	-0.0469	-1.0736	1.0688	-0.9216	1.4660
K_{I6}	0.4443	0.4272	-0.9840	-0.9851	-1.2142	-1.0563
K_{D1}	-	-	-	-	-0.3300	-1.8106
K_{D2}	-	-	-	-	-1.9281	-0.0179
K_{D3}	-	-	-	-	-1.2322	-1.4446
K_{D4}	-	-	-	-	-0.9383	-0.4666
K_{D5}	-	-	-	-	0.3864	-1.6739
K_{D6}	-	-	-	-	-1.5340	-1.0884
N_{C1}	-	-	-	-	54.5860	110.4305
N_{C2}	-	-	-	-	132.0739	84.7058
N_{C3}	-	-	-	-	22.7897	82.3165
N_{C4}	-	-	-	-	148.5366	118.7401
N_{C5}	-	-	-	-	285.8278	104.4742
N_{C6}	-	-	-	-	268.5511	105.0600
w11	-	0.5077	-	0.8984	-	0.1012
W22	-	0.7811	-	0.7284	-	0.7587
w12	-	0.2900	-	0.4068	-	0.1651

Table 6: Performance index with different objective functions and controller structure.

Performance index / Controller/Objective function	T_S(sec)			Peak Overshoot			ζ	ITAE
	ΔF_1	ΔF_2	ΔP_{tie}	ΔF_1	ΔF_2	ΔP_{tie}		
I controller: J_1	43.200	43.30	34.70	0.1646	0.1590	0.0261	0.0602	20.4615
I controller: J_2	40.40	42.20	29.60	0.1464	0.1480	0.0229	0.0616	21.0012
PI controller: J_1	26.80	28.10	17.30	0.1009	0.1150	0.0176	0.0824	5.4997
PI controller: J_2	19.50	18.00	12.30	0.0685	0.0398	0.0006	0.1245	7.6106
PIDF controller: J_1	12.90	16.08	13.77	0.0525	0.0301	0.0043	0.1846	3.9113
PIDF controller: J_2	4.21	3.80	6.45	0.0384	0.0360	0.0020	0.4448	4.6002

It can be seen from Table 6 that further improvements in the system performance is realized with suggested new objective function J_2 with PIDF controller. Time domain simulations are executed for step increase in demand of 10% is applied at t = 0 sec in area-1. The system performances are presented in Figs. 4-6 for objective function J_1. Figs. 4-6, it is illustrations that the improved system performance is achieved with suggested PIDF. For assessment the simulation results with same PIDF controller by the proposed modified J_2 and J_1 are also presented in Figs. 7-9. It is clearly observed from the Figs. 7-9 that best dynamic performance as well as better response is achieved by proposed approach J_2 correlated to J_1.

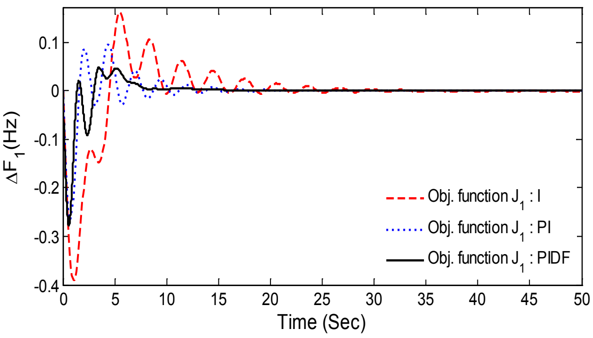

Fig. 4: ΔF_1 at 10 % change in area-1 (with objective function J_1).

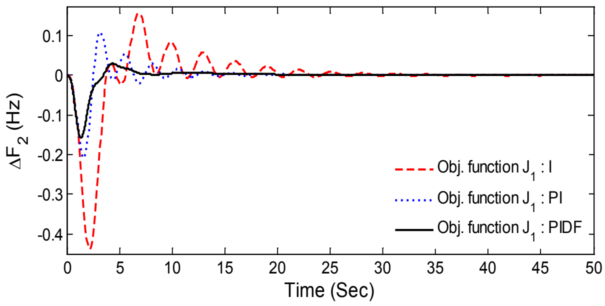

Fig. 5: ΔF_2 at 10 % change in area-1 (with objective function J_1)

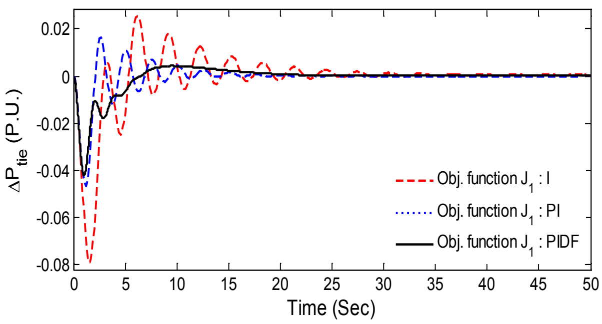

Fig. 6: ΔP_{tie} at 10 % change in area-1 (with objective function J_1).

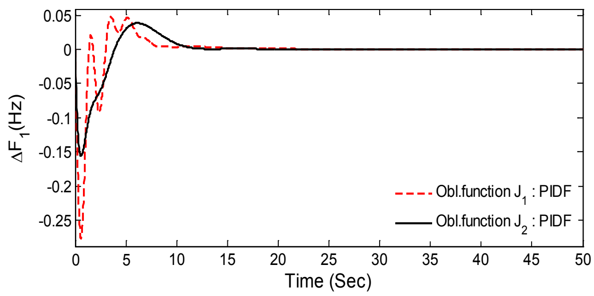

Fig. 7: ΔF_1 at 10 % change in area-1(J_1/J_2 objective functions).

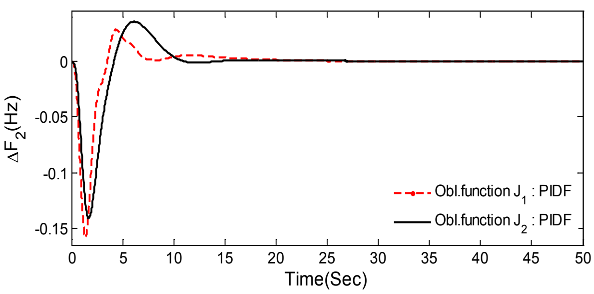

Fig. 8: ΔF_2 at 10 % change in area-1 (J_1/J_2 objective functions).

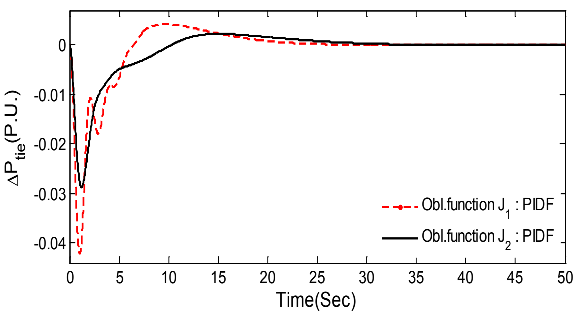

Fig.9 : ΔP_{tie} at 10 % change in area-1 (J_1/J_2 objective functions)

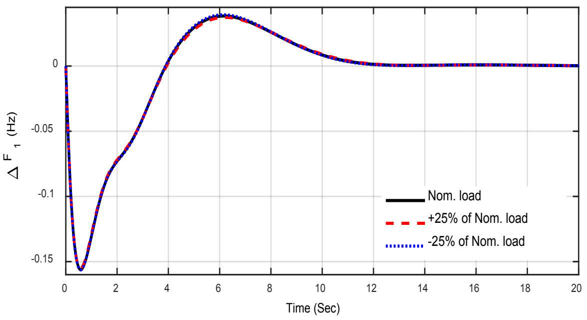

Fig.10: ΔF_1 with variation of loadings

5.3. Sensitivity Analysis

To assess the strength of the suggested method for extensive variations in the system parameters and working conditions, sensitivity analysis is carried out [4], [31], [32]. The nominal values varying from +25% to -25% in the working load condition and system parameters by considering one at a time (given in appendix). PIDF and objective function weights are tuned by proposed hybrid MDE-PS algorithm using modified objective function J_2 in all the cases. The optimized parameters (for a SLP of 10% at t = 0 sec in area-1) under the above varied conditions are provided in Table 7 and 8. The corresponding performance indexes are specified in Table 9. Table 9 obviously depicts that the system time constants and variations on operating loading conditions over the system performance are insignificant. As an illustration, frequency response of area-1 with ±25% variations in the loading conditions and speed governor time constant of thermal unit is illustrated in Figs. 10-11. From Figs. 10-11, it is observed that the deviation in operating load condition and system time constants on the system performance is insignificant. Thus it can be resolved that, the suggested control scheme offers a robust and stable control with variations in system parameters or system loading.

Table 7: Optimized gains by different situations.

	Loading condition		T_{SG}		T_{GH}		T_T	
	+25%	-25%	+25%	-25%	+25%	-25%	+25%	-25%
K_{P1}	-1.8499	-1.8455	-1.8229	-1.8239	-1.8434	-1.8437	-1.8258	-1.8455
K_{P2}	0.2363	0.2407	0.2462	0.2441	0.2353	0.2499	0.2386	0.2407
K_{P3}	-1.6062	-1.5987	-1.5979	-1.5966	-1.5942	-1.6075	-1.6050	-1.5987
K_{P4}	1.0469	1.0120	1.0398	1.0183	1.0401	1.0265	1.0131	1.0120
K_{P5}	0.7452	0.7403	0.7289	0.7233	0.7580	0.7226	0.7668	0.7403
K_{P6}	-0.6039	-0.6238	-0.6005	-0.6225	-0.5921	-0.6271	=-0.6182	-0.6238
K_{I1}	-0.8131	-0.8345	-0.8109	-0.8273	-0.8267	-0.8200	-0.8135	-0.8345
K_{I2}	-1.0158	-1.0257	-1.0254	-1.0167	-1.0251	-1.0081	-1.0165	-1.0257
K_{I3}	-1.5717	-1.5627	-1.5695	-1.5679	-1.5704	-1.5698	-1.5700	-1.5627
K_{I4}	-0.5308	-0.5200	-0.5220	-0.5382	-0.5385	-0.5308	-0.5562	-0.5200
K_{I5}	1.4689	1.4664	1.4628	1.4720	1.4724	1.4775	1.4799	1.4664
K_{I6}	-1.0484	-1.0477	-1.0107	-1.0601	-1.0374	-1.0796	-1.0769	-1.0477
K_{D1}	-1.8192	-1.8266	-1.8202	-1.8115	-1.8164	-1.8232	-1.8292	-1.8266
K_{D2}	-0.0517	-0.0437	-0.0569	-0.0296	-0.0250	-0.0114	-0.0439	-0.0437
K_{D3}	-1.4499	-1.4483	-1.4371	-1.4346	-1.4393	-1.4492	-1.4381	-1.4483
K_{D4}	-0.4886	-0.4778	-0.4871	-0.4873	-0.4811	-0.4723	-0.4867	-0.4778
K_{D5}	-1.6849	-1.6734	-1.6761	-1.6772	-1.6790	-1.6718	-1.6796	-1.6734
K_{D6}	-1.0740	-1.0893	-1.0745	-1.0758	-1.0892	-1.0756	-1.0746	-1.0893
N_{C1}	110.0727	110.6965	110.2176	110.1919	110.8969	111.5339	110.7926	110.6965
N_{C2}	84.3772	85.1970	85.2087	85.2899	84.1384	84.3918	85.4102	85.1970
N_{C3}	83.1551	83.4628	83.1111	82.9922	82.3823	82.0499	83.1171	83.4628
N_{C4}	119.2565	119.7416	119.2095	118.5329	119.1143	118.2635	119.5133	119.7416
N_{C5}	103.7295	103.6668	104.5854	104.4657	104.8942	103.6980	104.9910	103.6668
N_{C6}	106.2731	105.9261	105.0418	106.8986	106.2301	106.3791	106.9249	105.9261
w_{11}	0.1078	0.0933	0.1098	0.1093	0.1063	0.0919	0.1007	0.0933
W_{22}	0.7601	0.7687	0.7535	0.7831	0.7726	0.7700	0.7886	0.7687
W_{12}	0.1272	0.1374	0.1640	0.1214	0.1423	0.1179	0.1169	0.1374

Table 8: Tuned parameters with different operating conditions.

	T_{RH}		T_W		T_{CD}	
	+25%	-25%	+25%	-25%	+25%	-25%
K_{P1}	-1.8295	-1.8490	-1.8499	-1.8347	-1.8424	-1.8239
K_{P2}	0.2367	0.2385	0.2363	0.2381	0.2434	0.2441
K_{P3}	-1.6010	-1.6000	-1.6062	-1.6047	-1.6013	-1.5966
K_{P4}	1.0328	1.0729	1.0469	1.0340	1.0219	1.0183
K_{P5}	0.7650	0.7450	0.7452	0.7584	0.7682	0.7233
K_{P6}	-0.6135	-0.6035	-0.6039	-0.6257	-0.6296	-0.6225
K_{I1}	-0.8271	-0.8084	-0.8131	-0.8259	-0.7982	-0.8273
K_{I2}	-1.0165	-1.0306	-1.0158	-1.0301	-1.0048	-1.0167
K_{I3}	-1.5628	-1.5726	-1.5717	-1.5744	=-1.5792	-1.5679
K_{I4}	-0.5239	-0.5288	-0.5308	-0.5224	-0.5500	-0.5382
K_{I5}	1.4724	1.4712	1.4689	1.4723	1.4643	1.4720
K_{I6}	-1.0531	-1.0826	-1.0484	-1.0101	-1.0281	-1.0601
K_{D1}	-1.8175	-1.8167	-1.8192	-1.8110	-1.8287	-1.8115
K_{D2}	-0.0111	-0.0264	-0.0517	-0.0128	-0.0586	-0.0296
K_{D3}	-1.4332	-1.4415	-1.4499	-1.4305	-1.4318	-1.4346
K_{D4}	-0.4653	-0.4744	-0.4886	-0.4878	-0.4883	-0.4873
K_{D5}	-1.6857	-1.6825	-1.6849	-1.6805	-1.6822	-1.6772
K_{D6}	-1.0852	-1.0886	-1.0740	-1.0851	-1.0860	-1.0758
N_{C1}	111.8686	110.6628	110.0727	111.1796	111.8774	110.1919
N_{C2}	85.5904	84.8337	84.3772	85.4778	84.1562	85.2899
N_{C3}	82.9085	82.6716	83.1551	82.6388	83.9005	82.9922
N_{C4}	118.6888	118.4756	119.2565	119.6963	118.4842	118.5329
N_{C5}	103.2657	103.8004	103.7295	103.9873	103.4344	104.4657
N_{C6}	106.1225	106.9078	106.2731	105.2297	105.2190	106.8986
w11	0.0942	0.0939	0.1078	0.1062	0.1008	0.1093
W22	0.7547	0.7743	0.7601	0.7767	0.7601	0.7831
w12	0.1561	0.1193	0.1272	0.1329	0.1601	0.1214

Table 9: Performance index under varied conditions.

Parameter variation	%	Peak Overshoot			Settling time T_s(Sec)			ζ	ITAE
		ΔF_1	ΔF_2	ΔP_{tie}	ΔF_1	ΔF_2	ΔP_{tie}		
Nominal	0	0.0384	0.0360	0.0023	4.21	3.80	6.45	0.4448	4.6002
Loading condition	+25	0.0374	0.0349	0.0023	4.28	3.86	6.54	0.4589	4.6169
	-25	0.0393	0.0372	0.0023	4.20	3.81	6.47	0.4412	4.6081
T_{SG}	+25	0.0386	0.0365	0.0023	4.27	3.86	6.55	0.4487	4.6568
	-25	0.0387	0.0362	0.0023	4.19	3.79	6.47	0.4478	4.5910
T_{GH}	+25	0.0391	0.0369	0.0023	4.18	3.79	6.51	0.3994	4.6135
	-25	0.0383	0.0359	0.0023	4.17	3.77	6.44	0.5413	4.5955
T_T	+25	0.0393	0.0368	0.0024	4.14	3.74	6.59	0.3894	4.6179
	-25	0.0379	0.0354	0.0022	4.28	3.89	6.41	0.4859	4.5838
T_{RH}	+25	0.0408	0.0383	0.0025	4.01	4.60	6.63	0.4776	4.9690
	-25	0.0359	0.0340	0.0020	4.49	4.01	5.93	0.3342	4.1775
T_W	+25	0.0391	0.0357	0.0023	4.27	3.83	6.44	0.3752	4.5985
	-25	0.0379	0.0371	0.0023	4.27	3.86	6.66	0.5344	4.6699
T_{CD}	+25	0.0389	0.0365	0.0024	4.16	3.76	6.55	0.4113	4.6630
	-25	0.0380	0.0354	0.0023	4.22	3.82	6.45	0.4928	4.5739

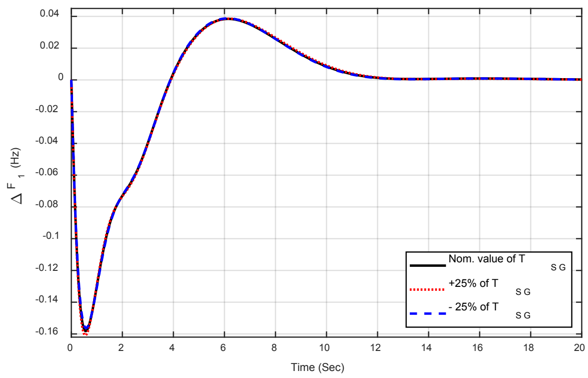

Fig: 11. ΔF_1 with varied T_{SG}.

5.4. Inclusion of Nonlinearities

To illustrate the ability of the suggested technique, the study is expanded with GRC, GDB and Time delay [33]. The generations rates for reheat thermal and hydro are about 3–10% pu MW/min and 270-360%/min respectively [34], [35]. The system become oscillatory due to the effect of GDB non-linearity and the typical value for steam turbines is 0.06% (0.036 Hz) [33]. The presentation of the system can be tainted and may become unstable due to time delay. In the current work time delay of 2 sec is considered.

To study the importance of the physical constraints, two scenarios (Scenario A and Scenario B) have been deliberate. In Scenario A, parameters obtained by the optimum PIDF controller by hMDE-PS method employing modified objective function without considering any physical constraints are tested in presence of nonlinearities which includes GRC's, GDB, and TD. In Scenario B, the PIDF controller parameters and weights of objective function J_2 are retuned employing proposed hybrid Pattern Search and MDE algorithm through improved objective function J_2. A 10 % SLP in area-1 is applied at t=0 sec and the system response is presented in Fig. 12. It is observed from Fig. 12 that the system becomes unstable for Scenario A but stable for Scenario B. The optimized gains under standard and different conditions with physical constraints are provided in Tables

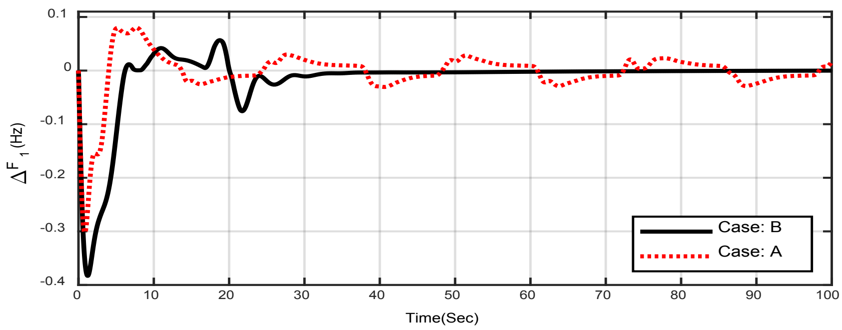

Fig. 12. ΔF_1 at 10 % change in area-1 (Scenario A & Scenario B)

Table 10: Optimized parameters under normal and different conditions with physical constraints.

Parameter	Nominal	Loading condition		T_{SG}		T_{GH}	
		+25%	-25%	+25%	-25%	+25%	-25%
K_{P1}	-0.3475	-0.3488	-0.3470	-0.3476	-0.3485	-0.3487	-0.3494
K_{P2}	-1.1864	-1.1887	-1.1862	-1.1868	-1.1888	-1.1871	-1.1887
K_{P3}	0.9981	0.9990	1.0000	0.9983	0.9999	0.9994	0.9991
K_{P4}	-1.8550	-1.8582	-1.8562	-1.8560	-1.8576	-1.8579	-1.8583
K_{P5}	1.1298	1.1314	1.1302	1.1301	1.1293	1.1312	1.1311
K_{P6}	-0.7339	-0.7356	-0.7342	-0.7351	-0.7368	-0.7354	-0.7332
K_{I1}	-0.3450	-0.3474	-0.3455	-0.3465	-0.3462	-0.3456	-0.3456
K_{I2}	0.3537	0.3539	0.3544	0.3543	0.3540	0.3540	0.3537
K_{I3}	-0.6025	-0.6059	-0.6060	-0.6035	-0.6037	-0.6021	-0.6030
K_{I4}	-1.4831	-1.4848	-1.4842	-1.4838	-1.4838	-1.4836	-1.4833
K_{I5}	-0.7881	-0.7913	-0.7921	-0.7920	-0.7924	-0.7907	-0.7892
K_{I6}	1.7833	1.7835	1.7838	1.7834	1.7840	1.7832	1.7838
K_{D1}	1.0849	1.0845	1.0844	1.0861	1.0856	1.0853	1.0869
K_{D2}	1.2897	1.2906	1.2917	1.2929	1.2897	1.2898	1.2907
K_{D3}	-1.5401	-1.5425	-1.5402	-1.5437	-1.5437	-1.5429	-1.5412
K_{D4}	0.8126	0.8129	0.8121	0.8148	0.8142	0.8141	0.8132
K_{D5}	0.3791	0.3799	0.3798	0.3810	0.3816	0.3809	0.3799
K_{D6}	-1.9543	-1.9567	-1.9559	-1.9561	-1.9569	-1.9541	-1.9563
N_{C1}	216.5290	217.9683	217.5196	216.8122	216.7089	217.8062	217.0396
N_{C2}	201.2404	202.7336	202.3342	201.9462	202.7829	202.0236	201.4248
N_{C3}	132.5354	133.2441	133.8128	132.6566	133.8639	133.6715	133.4258
N_{C4}	208.4307	209.8008	208.7939	209.6587	208.8630	209.6302	208.9688
N_{C5}	41.6651	42.5935	41.8836	42.2769	42.3878	42.3990	42.1081
N_{C6}	139.6429	141.8880	140.7089	140.6438	140.7127	140.9487	139.7644
w_{11}	0.1057	0.1060	0.1080	0.1073	0.1088	0.1050	0.1085
w_{22}	0.5710	0.5977	0.5750	0.5878	0.5708	0.5997	0.5837
w_{12}	0.2176	0.2704	0.2656	0.2175	0.2775	0.2381	0.2162

Table 11: Tuned parameters with varied conditions with physical constraints.

	T_T		T_{RH}		T_W		T_{CD}	
	+25%	-25%	+25%	-25%	+25%	-25%	+25%	-25%
K_{P1}	-0.3500	-0.3496	-0.3495	-0.3708	-0.3498	-0.3496	-0.3475	-0.3485
K_{P2}	-1.1882	-1.1881	-1.1878	-1.1855	-1.1888	-1.1872	-1.1878	-1.1886
K_{P3}	0.9990	0.9999	0.9996	1.0963	0.9991	0.9995	0.9985	0.9990
K_{P4}	-1.8588	-1.8585	-1.8578	-1.8934	-1.8575	-1.8583	-1.8554	-1.8588
K_{P5}	1.1305	1.1302	1.1312	1.1138	1.1310	1.1316	1.1302	1.1292
K_{P6}	-0.7354	-0.7368	-0.7350	-0.7137	-0.7361	-0.7346	-0.7363	-0.7345
K_{I1}	-0.3477	-0.3472	-0.3478	-0.3159	-0.3486	-0.3478	-0.3457	-0.3474
K_{I2}	0.3548	0.3559	0.3546	0.3139	0.3554	0.3557	0.3536	0.3536
K_{I3}	-0.6046	-0.6049	-0.6058	-0.6733	-0.6058	-0.6048	-0.6024	-0.6047
K_{I4}	-1.4831	-1.4835	-1.4849	-1.4331	-1.4830	-1.4845	-1.4845	-1.4843
K_{I5}	-0.7916	-0.7930	-0.7926	-0.7490	-0.7928	-0.7919	-0.7929	-0.7918
K_{I6}	1.7857	1.7836	1.7839	1.7663	1.7847	1.7840	1.7843	1.7853
K_{D1}	1.0849	1.0847	1.0868	1.0970	1.0870	1.0864	1.0844	1.0858
K_{D2}	1.2937	1.2931	1.2925	1.2656	1.2924	1.2918	1.2902	1.2930
K_{D3}	-1.5428	-1.5426	-1.5420	-1.5115	-1.5415	-1.5413	-1.5435	-1.5412
K_{D4}	0.8124	0.8136	0.8143	0.8128	0.8144	0.8141	0.8122	0.8128
K_{D5}	0.3790	0.3810	0.3812	0.3340	0.3806	0.3816	0.3792	0.3792
K_{D6}	-1.9562	-1.9548	-1.9541	-1.9510	-1.9552	-1.9541	-1.9548	-1.9562
N_{C1}	216.9483	217.4320	217.8093	217.6779	217.6884	217.4326	217.1704	217.1691
N_{C2}	201.6128	202.0309	202.5567	201.3809	202.4215	201.7448	202.4153	201.4230
N_{C3}	132.7610	132.8453	132.9439	133.4750	133.6978	133.1118	132.8922	133.5628
N_{C4}	209.1763	209.4397	208.4787	208.2975	209.9325	208.9302	209.5139	209.9711
N_{C5}	42.6143	42.0541	42.6029	41.5572	42.3894	42.6461	42.3778	42.2148
N_{C6}	140.9301	141.2938	141.5164	140.3469	140.4645	140.2118	139.7032	140.0120
w_{11}	0.1059	0.1067	0.1088	0.1117	0.1057	0.1084	0.1057	0.1050
w_{22}	0.5784	0.5987	0.5935	0.5890	0.5941	0.5782	0.5876	0.5783
w_{12}	0.2170	0.2432	0.2183	0.2109	0.2618	0.2513	0.2508	0.2458

Table 12: Performance index for Sensitivity analysis with physical constraint.

Parameter variation	% Change	Peak Overshoot			Settling time T_s(Sec)			ζ	ITAE
		ΔF_1	ΔF_2	ΔP_{tie}	ΔF_1	ΔF_2	ΔP_{tie}		
Nominal	0	0.0538	0.0482	0.0045	40.31	40.63	30.65	0.3058	50.5521
Loading condition	+25	0.0539	0.0494	0.0041	40.97	40.93	30.19	0.3124	50.7273
	-25	0.0622	0.0532	0.0067	40.14	40.23	30.02	0.2996	50.0044
T_{SG}	+25	0.0554	0.0602	0.0043	40.69	40.02	30.21	0.3061	50.8274
	-25	0.0489	0.0571	0.0024	40.95	40.32	30.19	0.3062	49.8352
T_{GH}	+25	0.0612	0.0508	0.0053	40.78	40.21	30.31	0.3059	51.3487
	-25	0.0462	0.0523	0.0070	40.10	40.53	29.47	0.3061	49.9012
T_T	+25	0.0486	0.0571	0.0072	40.35	40.43	30.88	0.3061	50.5805
	-25	0.0467	0.0512	0.0012	40.11	40.30	30.43	0.3060	50.0012
T_{RH}	+25	0.0532	0.0675	0.0045	40.15	40.77	30.51	0.3059	50.5229
	-25	0.0464	0.0461	0.0036	40.35	40.07	30.32	0.3056	49.7575
T_W	+25	0.0552	0.0519	0.0055	40.44	40.65	30.12	0.3059	50.9391
	-25	0.0588	0.0563	0.0024	40.06	40.45	30.19	0.3059	49.8208
T_{CD}	+25	0.0478	0.0513	0.0057	40.91	40.53	30.77	0.2854	50.9966
	-25	0.0504	0.0558	0.0037	40.78	40.11	29.58	0.3175	49.2938

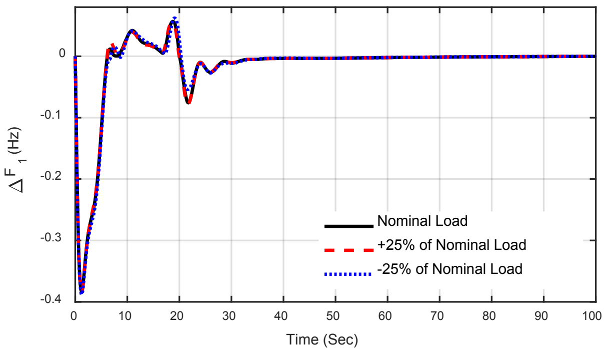

Fig. 13: ΔF_1 with different loading considering physical constraints.

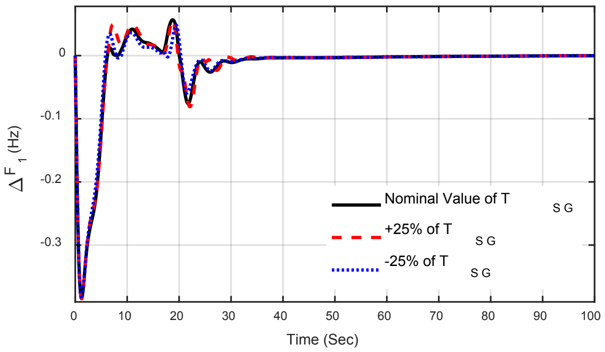

Fig. 14: ΔF_2 with varied T_{SG} considering physical constraints.

10 and 11. The performance index is presented in Table 12. It is found from Table 12 that the system performances satisfactory when the working load situation and system parameters are altered by ±25% from their nominal values. Further the efficacy of the suggested technique is also examined for some varied conditions. A 10% SLP in area-1 at t = 0 sec is considered and the system frequency deviation responses for the different situations are given in Figs. 13-14. It can be concluded from Figs. 13-14 that the proposed methods are robust and perform effectively.

6. Conclusions

Design and performance study of hybrid Modified Differential Evolution (MDE) method and Pattern Search (PS) for AGC of interconnected power systems is offered in this paper. Initially the integral control gains are optimized using an ITAE criterion for a two-area diverse source power system with thermal, hydro and gas power plants in each area. Studies are carried out to choose the strategy and controller parameters of DE. Also, an improved DE technique is suggested in which the DE step size (*F*) and crossover probability (*CR*) are different throughout the course. It concludes from studies that, the strategy DE/rand/1/bin wherever the DE controller parameter F is reduced exponentially from 1.0 to 0.002 and *CR* reduced exponentially from 1.0 to 0.02 with the number of population (*NP*) of 40 and generation (*G*) of 100 provides the greatest technique performance. PS is later applied to fine tune the greatest result delivered by MDE algorithm. Improved objective function and controller arrangement are then recycled and parameters are acquired using the suggested hybrid method. Supplementary, sensitivity analysis is executed by changing conditions from their nominal values. Lastly, the suggested method is applied to a nonlinear system such as TD, GRC and GDB.

Appendix

The investigated system nominal parameters are: [4]
$R_1 = R_2 = R_3 = 2.4$ Hz/p.u.; $B_1 = B_2 = 0.4312$ p.u., $T_{12} = 0.0433$, $a_{12} = -1$ MW/Hz; $T_{SG} = 0.08$sec, $T_t = 0.3$s, $K_r=0.3$; $T_r = 10$ s; $K_T = 0.543478$; $T_P= 1.49$ s; $K_{PS} =68.9566$ Hz/p.u. MW; $K_H = 0.326084$; $T_W= 1.0$s, $T_{RS} = 5$s, $T_{GH} = 0.2$s, $T_{RH} = 28.75$ s, $X_C = 0.6$s, $Y_C = 1$s, $T_F = 0.23$s, $T_{CD} = 0.2$s; $T_{CR} = 0.01$s, $K_G = 0.130438$, $c_g = 1$, $b_g =0.05$s.

References

[1] P. Kundur, *Power System Stability and Control*, Tata McGraw-Hill, New Delhi, India, (2009).
[2] O.I. Elgerd, *Electric Energy Systems Theory. An Introduction*, Tata McGraw-Hill, New Delhi, India, (2007).
[3] H. Bevrani, *Robust Power System Frequency Control*, New York, Springer, (2009).
[4] KPS. Parmar, S. Majhi & DP. Kothari (2012), Load frequency control of a realistic power system with multi-source power generation. *International Journal of Electrical Power & Energy Systems* 42, 426-433.
[5] Ibraheem, P. Kumar & DP. Kothari (2005), Recent philosophies of automatic generation control strategies in power systems. *IEEE Transactions on Power Systems* 20, 346-357.
[6] LC. Saikia, J. Nanda & S. Mishra (2011), Performance comparison of several classical controllers in AGC for multi-area interconnected thermal system. *International Journal of Electrical Power & Energy Systems* 33, 394-411.
[7] RK. Sahu, GT. Chandra Sekhar & S. Panda (2016), Automatic generation control of multi-area power systems with diverse energy sources using Teaching Learning Based Optimization algorithm. *Engineering Science and Technology, an International Journal* 19(1), 113-134.
[8] Y. Arya & N. Kumar (2017), Optimal control strategy-based AGC of electrical power systems: a comparative performance

analysis. *Optimal Control Applications and Methods* 38(6), 982–992.

[9] H. Shabani, B.Vahidi, & M. Ebrahimpour (2013), A robust PID controller based on imperialist competitive algorithm for load-frequency control of power systems. *ISA Transactions* 52(1), 88-95.

[10] S. Padhan, RK. Sahu, & S. Panda (2014), Application of firefly algorithm for load frequency control of multi-area interconnected power system. *Electric Power Components and Systems* 42(3), 1419-1430.

[11] S.M. Abd-Elazim & E.S. Ali (2018), Load frequency controller design of a two-area system composing of PV grid and thermal generator via firefly algorithm. *Neural Computing and Applications* 30(2), 607- 616.

[12] K. Jagatheesan, B. Anand, S. Samanta, N. Dey, V. Santhi, AS. Ashour & VE. Balas (2017), Application of flower pollination algorithm in load frequency control of multi-area interconnected power system with nonlinearity. *Neural Computing and Applications* 28 (1), 475-488.

[13] D. Guha, PK. Roy & S. Banerjee (2016), Load frequency control of interconnected power system using grey wolf optimization. *Swarm and Evolutionary Computation* 27, 97-115.

[14] RK. Sahu, S.Panda & S. Padhan (2015), A hybrid firefly algorithm and pattern search technique for automatic generation control of multi area power systems. *International Journal of Electrical Power & Energy Systems* 64, 9-23.

[15] R. Sivalingam, S. Chinnamuthu & SS. Dash (2017), A hybrid stochastic fractal search and local unimodal sampling based multistage PDF plus (1 + PI) controller for automatic generation control of power systems. *Journal of the Franklin Institute* 354 (12), 4762-4783.

[16] R. Stron & K. Price (1995), Differential evolution – A simple and efficient adaptive scheme for global optimization over continuous spaces. *Journal of Global Optimization* 11, 341-359.

[17] S. Das & PN. Suganthan (2011), Differential Evolution: A Survey of the State-of-the-Art. *IEEE Transactions on Evolutionary Computation* 15, 4-31.

[18] B. Janez, G. Saso, B. Borko, M. Marjan & Z. Viljem (2005), Self-Adapting Control Parameters in Differential Evolution: A Comparative Study on Numerical Benchmark Problems. *IEEE Transactions on Evolutionary Computation* 10, 646-657.

[19] A.K. Qin, VL. Huang & PN. Suganthan (2009), Differential Evolution Algorithm with Strategy Adaptation for Global Numerical Optimization. *IEEE Transactions on Evolutionary Computation* 13, 398-417.

[20] S.M. Islam, S.Das, S. Ghosh, S. Roy & PN. Suganthan (2012), An Adaptive Differential Evolution Algorithm with Novel Mutation and Crossover Strategies for Global Numerical Optimization. *IEEE Transactions on Evolutionary Computation* 42, 482-500.

[21] Y. Bao, Z. Hu & T. Xiong (2013), A PSO and Pattern Search based Memetic Algorithm for SVMs Parameters Optimization. *Neurocomputing* 117, 98-106.

[22] A.K. Al-Othman, A. Nabil, M.E. Ahmed, A. Sharidah, A. Hanan & A. Mekhaizim (2013), A hybrid real coded genetic algorithm – Pattern search approach for selective harmonic elimination of PWM AC/AC voltage controller. *International Journal of Electrical Power & Energy Systems* 44, 123-133.

[23] J. Liu & J. Lampinen (2005), A fuzzy adaptive differential evolution algorithm, Soft Computing-A Fusion of Foundations. *Methodologies and Applications* 9(6), 448-462.

[24] R. Gämperle, S.D. Müller & P. Koumoutsakos (2002), A parameter study for differential evolution, in Advances in Intelligent Systems. *Interlaken*, Switzerland: WSEAS Press 293-298.

[25] M.M. Ali, & A. Torn (2004), Population set-based global optimization algorithms: Some modifications and numerical studies. *Computers & Operations Research* 31(10), (2004) 1703-1725.

[26] S. Das, A. Konar & U.K. Chakraborty (2005), Two improved differential evolution schemes for faster global search. GECCO *'05 Proceedings of the 7th annual conference on Genetic and evolutionary computation,* Washington, DC, 991-998.

[27] U.K. Chakraborty, S. Das & A. Konar, Differential evolution with local neighborhood. *IEEE International Conference on Evolutionary Computation*, Vancouver, BC, Canada, (2006), 2042-2049.

[28] M.G.H. Omran, A. Salman, A.P. Engelbrecht, "Self-adaptive differential evolution, in *Lecture Notes in Artificial Intelligence*, Berlin, Germany: Springer-Verlag, (2005), 192-199.

[29] H.A. Abbass, The self-adaptive Pareto differential evolution algorithm. *Proceedings of the 2002 Congress on Evolutionary Computation.* CEC'02, 831-836.

[30] E.D. Dolan, R.M. Lewis & V. Torczon (2003), On the local convergence of pattern search. *SIAM Journal of Optimization* 14 (2), 567-583.

[31] S. Panda (2011), Robust coordinated design of multiple and multi-type damping controller using differential evolution algorithm. *International Journal of Electrical Power & Energy Systems* 33, 1018-1030.

[32] R. K. Sahu, S. Panda & UK. Rout (2013), DE optimized parallel 2-DOF PID controller for load frequency control of power system with governor dead-band nonlinearity. *International Journal of Electrical Power & Energy Systems* 49, 19-33.

[33] H. Golpîra, H. Bevrani & H. Golpîra (2011), Application of GA optimization for automatic generation control design in an interconnected power system. *Energy Conversion and Management* 52, 2247-2255.

[34] K.R. Sudha, Y.B. Raju, & A.C. Sekhar (2012), Fuzzy C-Means clustering for robust decentralized load frequency control of interconnected power system with generation rate constraint. *International Journal of Electrical Power & Energy Systems* 37, 58-66.

[35] S.R. Khuntia & S. Panda (2012), Simulation study for automatic generation control of a multi-area power system by ANFIS approach. *Applied Soft Computing* 12, 333-341.