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Multiobjective optimization using weighted sum Artificial Bee Colony algorithm for Load Frequency Control

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ABSTRACT

This paper presents the implementation of multiobjective based optimization of Artificial Bee Colony (ABC) algorithm for Load Frequency Control (LFC) on a two area interconnected reheat thermal power system. The ABC algorithm is currently being applied in many research works due to the local and global search capability of the algorithm. This paper uses the weighted sum approach of the ABC to optimize the PID controller's gains to provide a compromise between the frequency response's settling time and maximum overshoot. The composite objective function comprising both objectives is characterized by the performance criterions – Integral of Time Multiplied Absolute Error (ITAE) and Integral of Time Weighted Squared Error (ITSE). Analysis is carried out to determine the best weightage set for this investigation. A performance index based on Least Average Error (LAE) is formulated to calculate the index of each weightage set. In order to ensure effective compensation in the system output, the PID controllers for both areas are tuned simultaneously. The tuning performance of the algorithm is evaluated by comparing the performance of the proposed controller with conventional PI and PID controller. The robustness of the proposed algorithm is further investigated by evaluating the response of the system under simultaneous step load perturbation (SLP), changing load demand and collectively varying system parameters in the range of ±50%. The simulation result shows the dynamic response of the controller emphasizes on the compromise between the settling time and maximum overshoot of the frequency response. Furthermore, the proposed algorithm is robust enough to operate under different operating conditions and system parameter variations.

1. Introduction

The electrical power system is an interconnection of many important components which ensures successful transmission of power over a certain region or large area. Proper interaction between the generating, transmitting and distributing elements of the system is important in order to ensure successful operation and stability of the interconnected power system. The dynamics of the power system will have a consequence on the resultant transient response. As such, the sudden variation in active power demand will introduce dynamic changes in the system. The system's frequency which depends upon the active power has to be maintained at its nominal value. In an interconnected power system, the Load Frequency Control (LFC) is used to maintain the frequency and inter-area (tie-line) power based on its scheduled value. The frequency of the system is affected when the load generation equilibrium is not maintained. When there is a difference between the generated power and load demand, frequency excursion will occur. If the load demand of the system is greater than the generator's power, the frequency of the system will decrease. Control action has to be initiated as soon as possible to deal with large frequency excursions to prevent system instability. If the maximum frequency overshoot reaches the threshold level, load shedding process will be initiated automatically to maintain the nominal frequency. With respect to that, in order to ensure reliable system operation, the system settling time should be less and the maximum overshoot should be minimum [1].

Analysis on LFC has been extensive and new research are still ongoing on how to further enhance the control approach and operation of the LFC. Physical limitations, dynamic behavior and system non-linearities have spurred researchers to further enhance the modeling and design of LFC [2]. Different methods and strategies have been implemented by researchers to optimize the performance of LFC. The design methods can be categorized as classical methods, adaptive and variable structure methods, robust control approaches, intelligence based algorithms and digital control methods [3]. The classical methods are conventional

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control strategies which were limited due to their poor performance in dynamic response. Elgerd and Fosha reported that the conventional control strategy which is based upon heuristic knowledge and experience is workable in practice but there might be better strategies available [4]. In the adaptive and variable structure method, fuzzy logic has been commonly used as the gain scheduling algorithm. However the adaptive tuning method requires accurate model design as operating condition parameters have to be monitored before the fuzzy logic rules are implemented [5]. The robust control method which is very suitable for practical application, takes into account uncertainties and disturbance/variations in the system. Wang et al. has designed a robust controller based on the Riccati equation which provides stable performance for all allowable parameter uncertainties [6]. Digital control method deals with the implementation of LFC controller in the discrete mode. Due to the discrete nature of the controller, the trade-off between the system response and sampling rate has to be considered [7].

The intelligence based methods have gained much interest from researchers due to the capability of the search mechanism that tunes the controller based on the evaluated fitness function. The PID controller is commonly used due to its simple and efficient characteristics [8]. The selection process of the controller's gain is done without the knowledge of the system parameters. The performance indices are used as the selection criteria in the search process. The common performance indices used by the PID controllers are the Integral of Absolute Error (IAE), Integral of Squared Error (ISE), Integral of Time Multiplied Absolute Error (ITAE) and Integral of Time Weighted Squared Error (ITSE) [9]. In recent literatures regarding the implementation of artificial intelligence in LFC, researchers have used different algorithms to tune the controller's (PI and PID) gains. In 2008, Pothiya and Ngamroo proposed a fuzzy logic based PID controller for LFC. In order to tune the PID gains, the multiple tabu search (MTS) was utilized [10]. Shayeghi designed a multi stage fuzzy controller based on particle swarm optimization (PSO) [11]. Both researchers considered the ITAE cost function. Nanda et al. in 2009 highlighted the application of bacterial foraging (BF) in optimizing several control parameters for an interconnected three area thermal system with unequal generating parameters [12]. The ISE cost function was used. In 2010, Gautam and Goyal presented the implementation of improved PSO (IPSO) to optimize the parameters of the PI controller based on the ISE cost function [13]. Ali and Abd-Elazim in 2011 investigated the application of BF in optimizing the PI controller by using the ITAE cost function [14]. In 2012, Gozde et al. used the Artificial Bee Colony (ABC) algorithm to tune PI and PID controller by investigating the controller's performance on each criterion – IAE, ISE, ITAE and ITSE [15]. Daneshfar and Bevrani introduced a multiobjective optimization method using Genetic Algorithm (GA) to tune the PI controllers [16]. The objective function for the multi area system is based upon the absolute value of Area Control Error (ACE) at the particular time frame. In order to select the fitness function, a vector evaluated objective function is calculated and selection is done based on this vector valued cost function.

Based on the previous work [9–14], it can be evaluated that only a single criterion (settling time or maximum overshoot) is used for optimizing the controller's parameters. Thus, with single objective optimization, only one criterion will be optimized in the expense of other criterion. Different than the previous work, the main objective of this paper is to implement multiobjective optimization in order to obtain a good compromise between the settling time and maximum overshoot in the frequency deviation step response.

The ABC algorithm which was developed by Karaboga is based on the foraging behavior of honey bees. It is a simple and robust algorithm which is capable of solving even complex combinatorial optimization problems [17]. The ABC algorithm has a robust

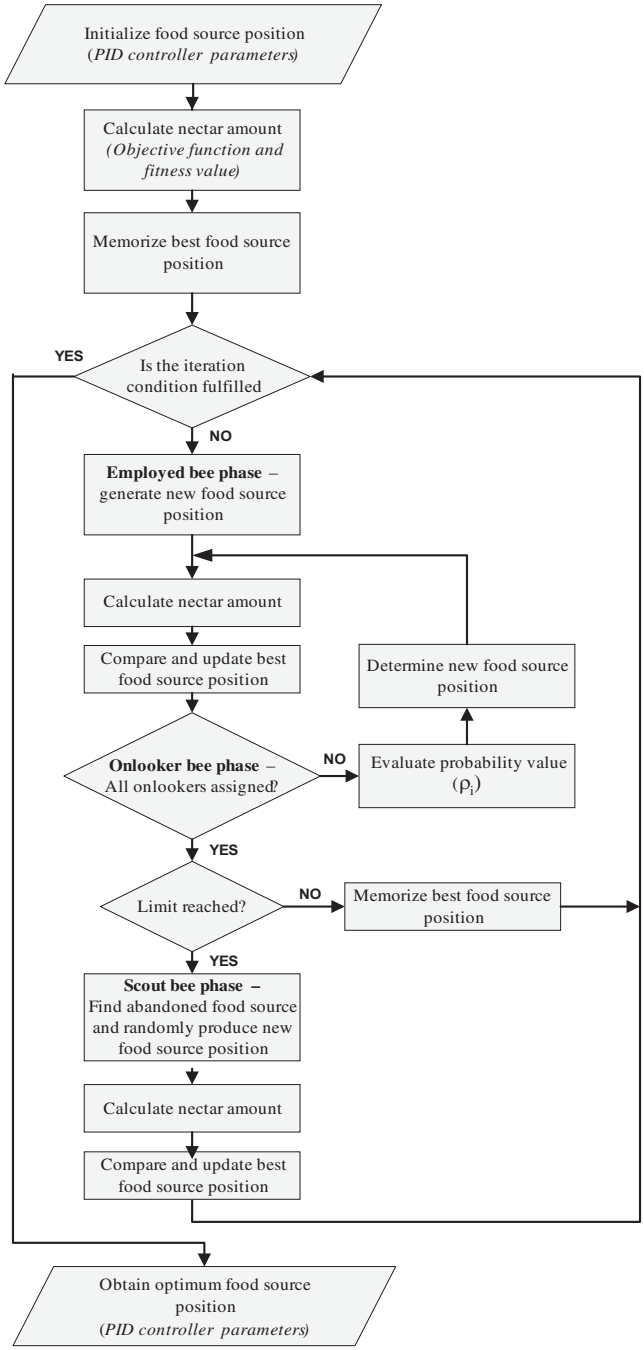

Fig. 1. ABC optimization process flowchart.

searching capability which incorporates the exploitation and exploration of the search space [18]. The exploitation process is represented by the employed and onlooker bee phase and the exploration process is represented by the scout bee phase. The triple search capability of the ABC algorithm based on the search phases of the three groups of bees prevents stalling of solution and further enhances the search process in finding the optimum value [19]. As such, the multiobjective optimization using weighted sum ABC algorithm is investigated in this study. A performance index based on Least Average Error is formulated to evaluate the tuning performance of each weightage set. This paper also discusses how the PID controller gains for both areas are tuned simultaneously based on the objective function. The robustness of the proposed algorithm is investigated by applying simultaneous

SLP in both areas. The ABC tuned PID controller is also investigated comparatively by using a conventional PI and PID controller. The efficiency of the controller is further tested by changing the load demand and collectively varying the system parameters.

2. Background

2.1. Artificial Bee Colony (ABC) algorithm

Artificial Bee Colony (ABC) is a meta heuristic algorithm based on swarm intelligence [20]. Swarm based optimization uses population based on nature inspired interacting agents. The action of the honey bees foraging is the main element of the ABC algorithm. The ABC algorithm is well suited to solve multidimensional optimization problems. The three main groups of bee present in the colony are employed, onlooker and scout bees.

In the search process, there are three main steps. Initially, the employed bees are moved to the food sources which are selected randomly. The position of the food source represents a possible solution to the optimization problem. The nectar amount of the food source which represents the value of the objective function is calculated. The objective function value determines the quality of the solution. The onlooker bees are deployed to the food source using probability based selection. The better the value of the objective function means the higher the probability of onlooker bees selecting that particular food source. The greedy selection scheme is used to update food source position. The employed bee modifies the position of the food source and the objective function value of the modified solution is compared with the previous objective function value. If the modified solution's objective function value is higher, the modified food position and objective function value is updated, replacing the older values. In order to produce the modified food solution, the following expression is used:

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \tag{1}$$

where i represents the current iteration while j and k are random numbers with the condition that $k \neq i$. ϕ_{ij} is a random number in the range of [−1 to 1]. Based on Eq. (1) it can be seen that as the step size (difference between x_{ij} and x_{kj}) reduces, the changes associated with the food source, x_{ij} reduces as well. This will help the algorithm narrow down to the solution by adaptively reducing the step size as the optimum solution approaches. The modified PID parameter v_{ij} will then be used as the modified food source for further evaluation. The onlooker bee selects a food source based on the food source's probability, ρ_i:

$$\rho_i = \left(\frac{\alpha(fit_i)}{\max(fit_{overall})}\right) + \beta \tag{2}$$

where fit_i represents the fitness value of the solution i as evaluated by the employed bees, and $\max(fit_{overall})$ represents the maximum fitness value from the overall fitness derived from the employed bee phase ($fit_{overall} = fit_i, fit_{i+1}, \ldots, fit_{FN}$, where FN represents the total number of food source). α and β represents the randomization variable which are typically in the range of [0–1]. The variable α and β are related based on the following expression:

$$\beta = 1 - \alpha \tag{3}$$

where α is chosen as 0.9 and β as 0.1. The exploitation of food source carried out by the employed and onlooker bees is then heightened through the exploration of food source by the scout bee phase. If the position of the food source cannot be improved through a certain number of cycles, the food source is abandoned. The abandoned food source is then substituted with a new food source which is randomly generated by the scout bee phase. The new food source which is randomly generated is then tested by the scout bee phase to determine if better solution exists compared to the existing solution. If it does, then the food position and objective function is updated. The greedy selection scheme and the random selection scheme increases the local and global search capability of the algorithm [21].

2.2. Multiobjective optimization approach

The basic ABC algorithm has been implemented in single objective function for Load Frequency Control. One of the easiest and practical approaches towards multiobjective optimization is through weighted sum method. In the weighted sum approach, the ABC algorithm is modified to enable multiobjective optimization. Marler and Arora provided a detail insight on how the weighted sum can be used to represent the preference in choice by selection of weight values in multiobjective optimization (MOO) [22]. Hemamalini and Simon implemented the multiobjective Artificial Bee Colony algorithm using the weighted sum method. The weighted sum approach treats the multiobjective optimization as composite objective function [23]. The composite objective function is expressed as follows:

$$U = \sum_{i=1} w_i F_i(x) \tag{4}$$

where w_i is the positive weight values. Minimizing Eq. (4) will provide a sufficient condition for optimal multiobjective solution to be found. Since the objective of this research is to provide a compromise between the maximum overshoot and settling time of the frequency response, the following composite objective functions is considered:

$$U = w_1 F_1(x) + w_2 F_2(x) \tag{5}$$

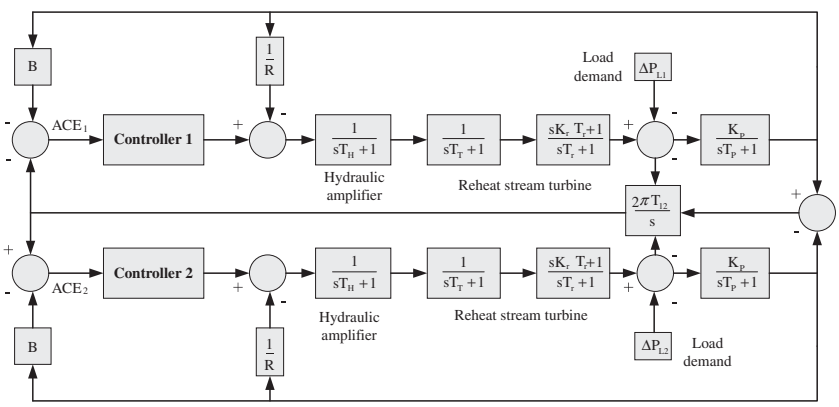

Fig. 2. Two area interconnected reheat thermal power system.

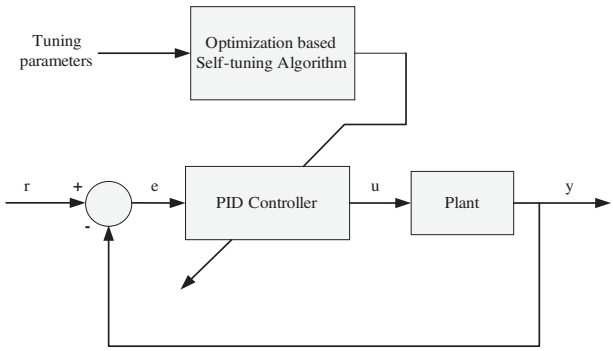

Fig. 3. Self-tuning algorithm.

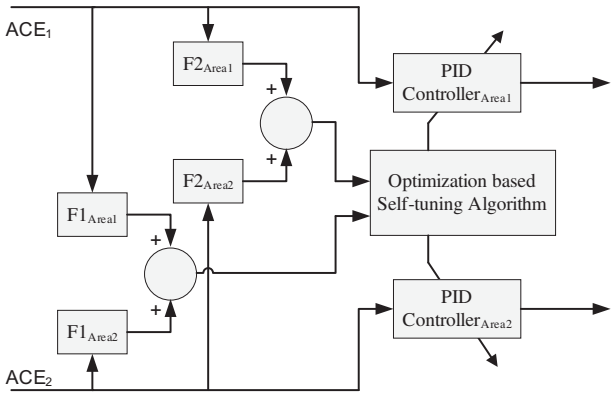

Fig. 4. Simultaneous tuning algorithm.

where w_1 and w_2 is the assigned weights and F_1 = *ITAE* and F_2 = *ITSE*. The variable w_1 and w_2 are related based on the following expression:

$$w_2 = 1 - w_1 \tag{6}$$

where w_1 is chosen is in the range of [0–1].

Using the weighted approach, the significance of the objective function can be tuned according to system requirement.

In order to evaluate the fitness of the composite objective function, min max normalization for the objective function is carried out. The normalization is required in order for the objective function to be scaled within a specified range. The following normalization formula is used [24]:

$$fit_i' = \frac{fit_i - \min(fit_{overall})x\delta}{\max(fit_{overall}) - \min(fit_{overall})x\delta} \tag{7}$$

where fit_i represents the fitness to be normalized and $fit_{overall}$ represents the overall fitness. δ is chosen as 0.999 and is used to avoid zeroes during normalization process. The flowchart of ABC optimization process is shown in Fig. 1 [25]:

The flowchart depicts how the PID controller optimization using weighted sum ABC is carried out. The PID parameters (K_{p1}, T_{i1}, T_{d1}, K_{p2}, T_{i2}, T_{d2}) for both controllers are initialized randomly and the weightage set (w_1 and w_2) are assigned. The objective function and fitness value is evaluated and normalized. The best set of PID parameters is memorized. In the employed bee phase, the food source position is modified using Eq. (1). The modified set of PID parameters is generated and the controller's objective function and fitness value is evaluated and normalized. If better solution is found, then the food source position is updated. In the onlooker bee phase, if all the onlookers have not been assigned, then the onlooker bees are probalistically selected. The food source position is then altered and a modified set of PID parameters is generated. The controller's objective function and fitness value is evaluated and normalized. If better solution is found, then the food source position is updated. If the limit is reached, the scout bee phase determines the abandoned food source and generates new food source position randomly. The best food source position is updated and memorized until the iteration condition is fulfilled.

2.3. System investigated

The AGC system of a two area interconnected reheat thermal power system is investigated in this multiobjective optimization as shown in Fig. 2. This model comprises of two reheat steam turbines and the system parameters are given in Appendix. Controller 1 and controller 2 are PID controllers.

The proportional gain (K_p), integral time constant (T_i) and derivative time constant (T_d) are the parameters tuned based on the area control error signal ($ACE_{i,i=1,2\ldots}$). The output of the controllers, u_1 and u_2 are expressed as

$$u_1 = K_{p1}\left(ACE_1 + \frac{ACE_1}{sT_{i1}} + sT_{d1}ACE_1\right) \tag{8}$$

$$u_2 = K_{p2}\left(ACE_2 + \frac{ACE_2}{sT_{i2}} + sT_{d2}ACE_2\right) \tag{9}$$

The integral gain (K_i) and derivative gain (K_d) of the controller

$$K_i = \frac{K_p}{T_i} \tag{10}$$

$$K_d = K_p * T_d \tag{11}$$

ACE signal which is an essential component of the Automatic Generation Control (AGC) contains information on the frequency deviation (Δf) and tie line power deviation ($\Delta Ptie$). Each area will have its own ACE.

$$ACE_1 = \Delta P_{tie1-2} + B_1\Delta f_1 \tag{12}$$

$$ACE_2 = \Delta P_{tie2-1} + B_2\Delta f_2 \tag{13}$$

When a step load perturbation is experienced in any area, the resultant ACE signal is used to invoke controller's action to compensate the error. The main objective of the controller is to regulate the ACE and drive it to zero as fast as possible. The self-tuning algorithm implemented using the optimization algorithm tunes the controller gains according to the respective area's ACE.

2.4. Objective function

The transient closed loop response of LFC can be evaluated by the using the error criterions such as IAE, ISE, ITAE and ITSE. These cost functions are evaluated as per following:

$$IAE = \int_0^t |ACE_i|dt \tag{14}$$

$$ISE = \int_0^t (ACE_i)^2 dt \tag{15}$$

$$ITAE = \int_0^t t.|ACE_i|dt \tag{16}$$

$$ITSE = \int_0^t t.(ACE_i)^2 dt \tag{17}$$

Table 1
Optimal PID controller gains and system performance at different weights with SLP in Area 1.

w_1	w_2	Area 1			Area 2			System performance		
		K_{p1}	T_{i1}	T_{d1}	K_{p2}	T_{i2}	T_{d2}	Settling time (s)	Max. overshoot (Hz)	η_{LAE}
1	0	2.0000	0.2795	0.6535	2.0000	0.4930	1.0406	5.9320	−0.0035	7.74
0.9	0.1	2.0000	0.2765	0.6797	2.0000	0.4978	1.0474	6.0000	−0.0034	8.44
0.8	0.2	2.0000	0.2617	0.7406	2.0000	0.5059	1.0793	8.5374	−0.0032	9.97
0.7	0.3	2.0000	0.2589	0.7509	2.0000	0.5095	1.0815	8.5772	−0.0032	10.23
0.6	0.4	2.0000	0.2412	0.8203	1.9999	0.4669	1.2024	8.7552	−0.0030	12.15
0.5	0.5	2.0000	0.2401	0.8337	1.9969	0.4706	1.2010	8.8009	−0.0030	12.56
0.4	0.6	2.0000	0.2370	0.8931	1.9999	0.4603	1.2819	9.0202	−0.0029	14.31
0.3	0.7	2.0000	0.2047	1.0620	1.9985	0.6016	1.6998	9.1938	−0.0026	17.23
0.2	0.8	2.0000	0.2000	1.1243	1.9988	0.6255	1.6678	9.3358	−0.0025	17.36
0.1	0.9	1.9998	0.2000	1.2082	2.0000	0.6585	1.6425	9.6431	−0.0023	16.07
0	1	2.0000	0.2000	1.3349	2.0000	0.2475	1.9972	10.0889	−0.0022	10.59

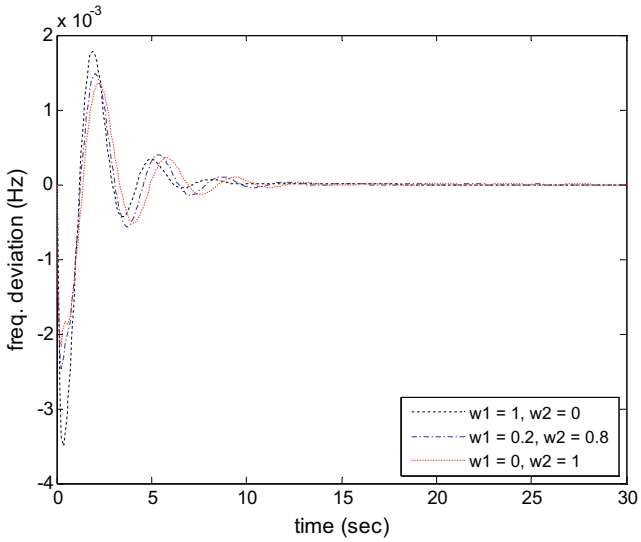

Fig. 5. Frequency deviations in Area 1 with SLP in Area 1.

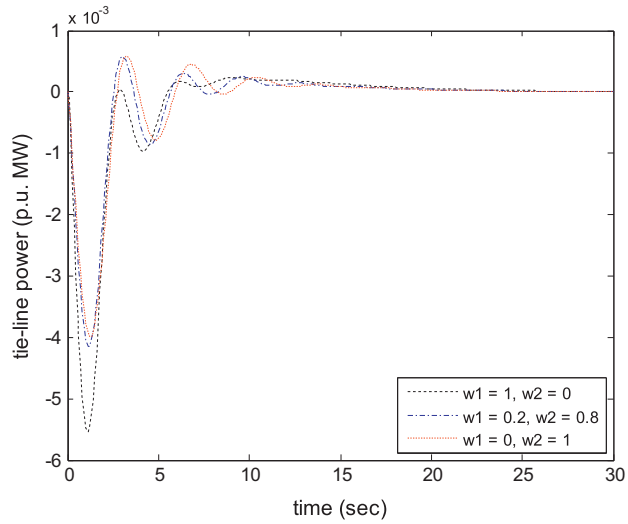

Fig. 7. Tie-line power changes with SLP in Area 1.

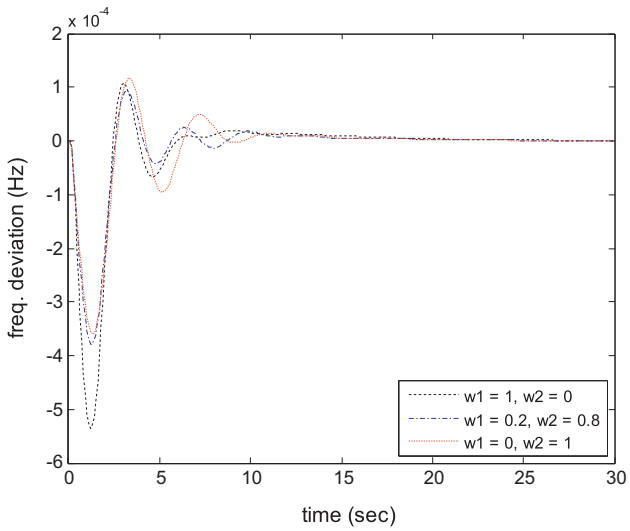

Fig. 6. Frequency deviations in Area 2 with SLP in Area 1.

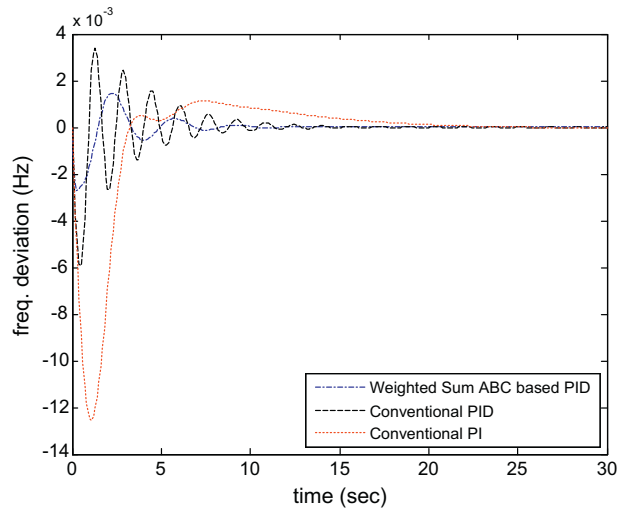

Fig. 8. Frequency deviations in Area 1 by using ABC based PID and conventional PI and PID controller.

The selection of error criterion as the objective function depends on the type of response desired because different error criterions will exhibit different system performance and output. The ISE exhibits smaller overshoots albeit longer settling time. IAE allows larger overshoots with shorter settling time compared to ISE. ITAE and ITSE error criterions impose a time multiplier which will allow initial deviations but will penalize errors occurring later in time [26].

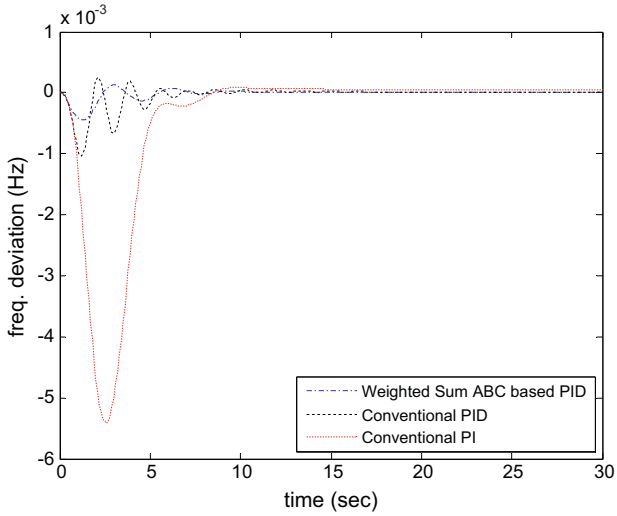

Fig. 9. Frequency deviations in Area 2 by using ABC based PID and conventional PI and PID controller.

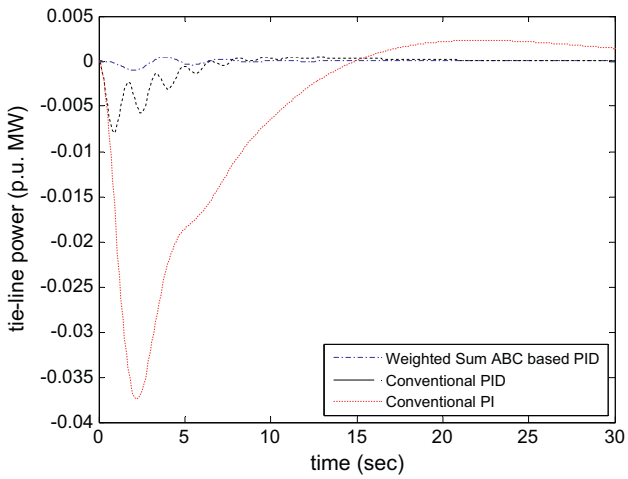

Fig. 10. Tie-line power changes by using ABC based PID and conventional PI and PID controller.

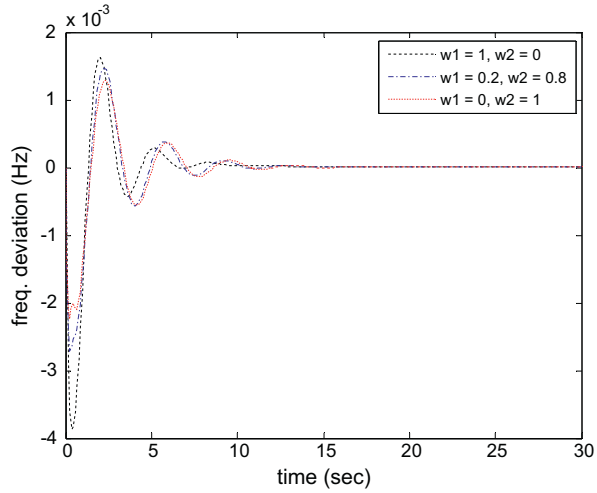

Fig. 11. Frequency deviations in Area 1 with SLP in both areas.

The self-tuning algorithm introduced by [27] is a gain/parameter scheduling technique for the controller as seen in Fig. 3. This technique is very robust and easy to implement. The parameters of the controller are tuned continuously to accommodate the changes in the system. In the interconnected reheat thermal power system, the plant represents the system and generator parameters. The PID controller is used to control the frequency of the system. The input of the controller is based on ACE of both areas. Considering the ACE of both areas, simultaneous tuning for both PID controllers is carried out as shown in Fig. 4. SLP applied in Area 1 will influence a change in Area 2's step response and vice versa. As such, simultaneous tuning of the controllers will ensure that proper control action is provided in both areas. The PID tuning range for this model is taken between the range of [0.2, 2] as described by researchers [15,27].

The performance indices of each area are summed and resultant composite objective function Eq. (5) is tuned by the optimization algorithm.

$$F_1(x) = F1_{Area1} + F1_{Area2} \tag{18}$$

$$F_2(x) = F2_{Area1} + F2_{Area2} \tag{19}$$

Table 2
Optimal PID controller gains and system performance at different weights with SLP in both areas.

w_1	w_2	Area 1			Area 2			System performance		
		K_{p1}	T_{i1}	T_{d1}	K_{p2}	T_{i2}	T_{d2}	Settling time (s)	Max. overshoot (Hz)	η_{LAE}
1	0	2.0000	0.3050	0.5731	2.0000	0.3051	0.5728	6.1082	−0.00387	6.92
								6.1082	−0.00388	
0.9	0.1	2.0000	0.3040	0.5816	2.0000	0.3040	0.5818	6.1364	−0.00385	7.11
								6.1368	−0.00384	
0.8	0.2	2.0000	0.3008	0.6028	2.0000	0.3008	0.6027	6.1943	−0.00377	7.58
								6.1943	−0.00377	
0.7	0.3	2.0000	0.2971	0.6236	2.0000	0.2972	0.6233	6.2429	−0.00371	8.04
								6.2424	−0.00371	
0.6	0.4	2.0000	0.2912	0.6584	2.0000	0.2911	0.6589	6.3188	−0.00359	8.80
								6.3194	−0.00359	
0.5	0.5	2.0000	0.2752	0.6963	2.0000	0.2872	0.7100	8.7367	−0.00347	9.55
								9.0830	−0.00344	
0.4	0.6	2.0000	0.2664	0.8480	2.0000	0.2278	0.8304	9.5868	−0.00305	12.56
								8.8063	−0.00307	
0.3	0.7	2.0000	0.2090	0.9165	2.0000	0.2618	0.9178	8.8190	−0.00287	13.89
								9.7975	−0.00288	
0.2	0.8	2.0000	0.2383	1.0136	2.0000	0.2000	1.0122	9.8949	−0.00271	14.69
								9.0850	−0.0027	
0.1	0.9	2.0000	0.2000	1.1637	2.0000	0.2000	1.1636	9.8034	−0.00245	13.05
								9.8033	−0.00245	
0	1	2.0000	0.2000	1.3102	2.0000	0.2000	1.3102	10.3430	−0.00224	10.30
								10.3430	−0.00224	

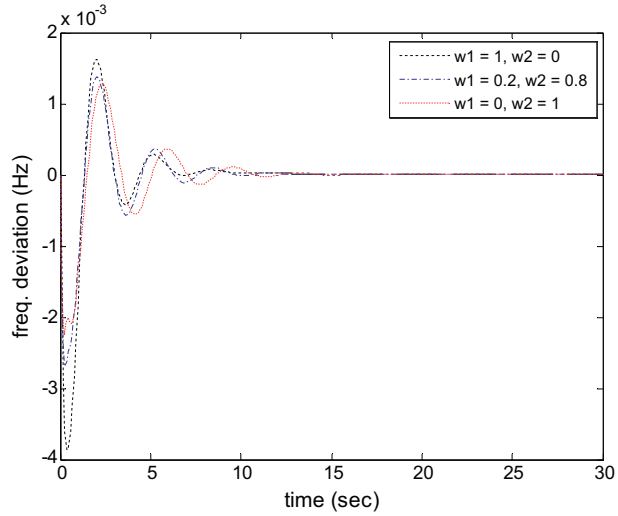

Fig. 12. Frequency deviations in Area 2 with SLP in both areas.

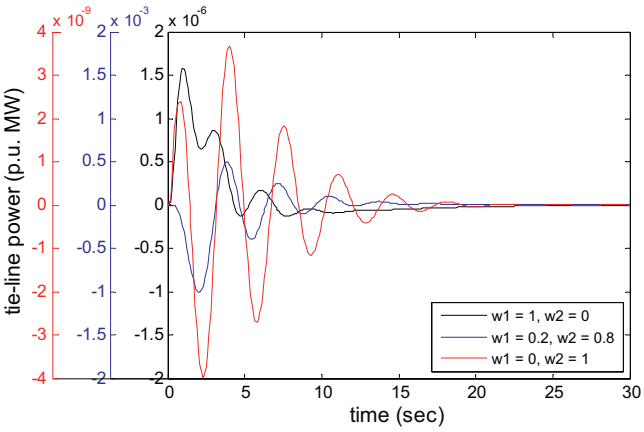

Fig. 13. Tie-line power changes with SLP in both areas.

Table 3
Weightage set and corresponding performance index based on LAE by varying load demand in the range of ±50%.

w_1	w_2	η_{LAE}			
		$\Delta P_L = +50\%$	$\Delta P_L = +25\%$	$\Delta P_L = -25\%$	$\Delta P_L = -50\%$
1	0	7.79	7.20	7.09	7.42
0.9	0.1	8.09	7.57	7.13	8.01
0.8	0.2	8.92	7.88	7.96	8.49
0.7	0.3	9.14	8.31	8.46	8.83
0.6	0.4	9.76	9.44	8.80	9.45
0.5	0.5	9.94	9.49	9.76	12.91
0.4	0.6	11.74	12.08	11.89	12.20
0.3	0.7	13.67	12.88	13.89	15.63
0.2	0.8	15.62	15.05	15.22	16.32
0.1	0.9	13.65	14.16	13.83	15.69
0	1	8.96	9.96	8.83	7.84

2.5. Weightage value selection and performance index

In order to assign the proper weightage values in Eq. (5), an investigation is carried out by varying the value w_1 from 1 to 0 with a step size of 0.1. This is done to observe the significance of each weightage set (w_{set}) towards the objective function. To evaluate the performance of each weightage set, a performance index based on the Least Average Error (LAE) is formulated. The LAE is calculated by:

$$LAE = \frac{\left(\frac{F_{1,w_{set,i}} - \min(F_{1,overall})}{\min(F_{1,overall})}\right) + \left(\frac{F_{2,w_{set,i}} - \min(F_{2,overall})}{\min(F_{2,overall})}\right)}{2} \tag{20}$$

where $F_{1,wset,i}$ represents ITAE value and $F_{2,wset,i}$ represents ITSE value at weightage set i (where $i = 1, 2, \ldots, 11$). $F_{1,overall}$ and $F_{2,overall}$ represent the overall ITAE and ITSE values. The performance index based on LAE (η_{LAE}) is expressed as:

$$\eta_{LAE} = \frac{1}{LAE} \tag{21}$$

In order to test the implementation of the multiobjective ABC algorithm in LFC, there are four different optimization cases in which the controller with the proposed algorithm was employed. In all these four cases, the PID controller parameters for both areas are tuned simultaneously. In Case I, the nominal step load perturbation (SLP) of 1% is applied in Area 1 alone. In Case II, the SLP is applied to both areas at the same time. In Case III, the SLP in Area 2 is maintained at 1% while the SLP in Area 1 is varied in the range of ±50% with a step size of 25%. Finally in Case IV, the nominal SLP is applied for both areas and the system parameters are varied collectively for Area 1 in the range of ±50% with a step size of 25% while the system parameters in Area 2 are maintained.

3. Simulation results

The multiobjective ABC algorithm is applied to optimize the gains of the PID controller. Off line tuning method is used to optimize the proportional (K_p), integral (K_i) and derivative (K_d) gain of the controller. The modeling and optimization process is carried out using MATLAB software version 7.10. The model of the two area interconnected reheat thermal power system is designed in Simulink and the controller optimization is executed through an M-file script. Referring to [28], SLP can occur either in a single area or in all areas simultaneously.

3.1. Case I – SLP in Area 1

An SLP of 1% (0.01 pu MW) is applied in Area 1 initially to test and evaluate the effectiveness of the optimized controller. The weightage set is varied in the range of 0 to 0.1 with a step size of 0.1. The PID controller gain and system performance are shown in Table 1 and Figs. 5–7.

The results show that when the weights are defined at their extremes, single objective optimization is achieved. When $w_1 = 1$ and $w_2 = 0$, ITAE is the effective objective function and it can be observed that the settling time is fast but the maximum overshoot value is large. In the other extreme, when $w_1 = 0$ and $w_2 = 1$, ITSE is the effective objective function in which the overshoot is minimized while the settling time is slower. These results are in accordance to the literature discussed above. Based on the highest η_{LAE} value observed in Table 1, the weightage set of $w_1 = 0.2$ and $w_2 = 0.8$ is chosen as the best combination.

In order to further ascertain and verify the tuning performance of the proposed controller, the system response of controller at the proposed weightage set ($w_1 = 0.2$ and $w_2 = 0.8$) is compared with the conventional PI and PID controller and the system response is shown in Figs. 8–10.

It is evidently clear that the proposed controller outperforms the conventional PI and PID controller as the proposed controller is able to settle the system with lower overshoot value and settling time with less oscillation.

Table 4
Optimal PID controller gains and system performance with varying load demand in the range of ±50%.

ΔP_L	Area 1			Area 2			System performance	
	K_{p1}	T_{i1}	T_{d1}	K_{p2}	T_{i2}	T_{d2}	Settling time (s)	Max. overshoot (Hz)
+50%	2.0000	0.2239	1.0966	2.0000	0.2000	0.9048	9.8261	−0.00384
							8.5306	−0.00294
+25%	2.0000	0.2403	1.0350	2.0000	0.2000	0.9357	9.8898	−0.00333
							8.6935	−0.00284
−25%	2.0000	0.2000	0.9174	2.0000	0.2333	1.0515	8.6114	−0.00216
							9.8310	−0.00263
−50%	1.9997	0.2000	0.8264	2.0000	0.2363	1.0283	8.1506	−0.00158
							9.7005	−0.00266

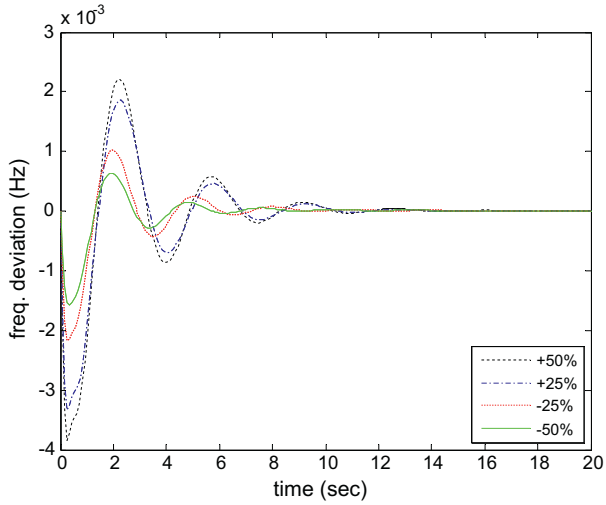

Fig. 14. Frequency deviations in Area 1 with varying load demand in the range of ±50%.

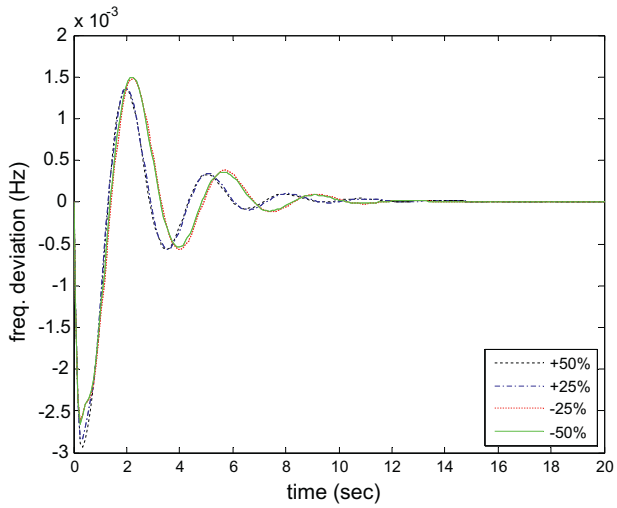

Fig. 15. Frequency deviations in Area 2 with varying load demand in the range of ±50%.

3.2. Case II – SLP in both areas

In order to test the robustness of the controller, an SLP of 1% (0.01 pu MW) is applied in both areas simultaneously. The weight values are varied and the PID controller gain and system performance are shown in Table 2 and Figs. 11–13.

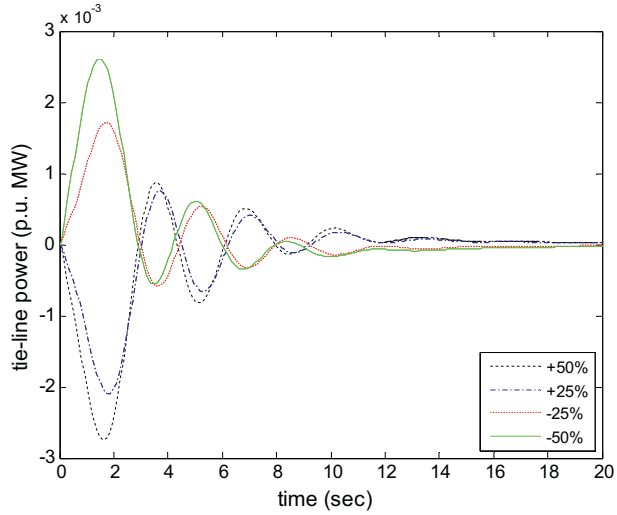

Fig. 16. Tie-line power changes with varying load demand in the range of ±50%.

Table 5
Weightage set and corresponding performance index based on LAE by collectively varying system parameters in the range of ±50%.

w_1	w_2	η_{LAE} System parameter variation			
		+50%	+25%	−25%	−50%
1	0	6.52	7.71	6.73	11.02
0.9	0.1	8.14	8.62	7.25	11.72
0.8	0.2	8.01	9.82	7.97	11.66
0.7	0.3	8.42	11.79	8.08	12.09
0.6	0.4	7.71	11.59	7.88	12.60
0.5	0.5	11.05	12.04	8.67	16.84
0.4	0.6	12.91	15.48	9.38	16.05
0.3	0.7	14.82	17.22	10.06	16.65
0.2	0.8	15.37	17.87	10.13	16.89
0.1	0.9	14.20	15.76	8.55	14.51
0	1	8.15	10.10	4.36	6.29

In the multi controller optimization, both the PID controllers are optimized at the same time and similar system performance is observed. Similar to case I, when $w_1 = 0.2$ and $w_2 = 0.8$, the highest value of η_{LAE} is obtained. The controller is able to respond to load demands in both areas effectively without affecting the system performance.

3.3. Case III – SLP in both areas with varying load demand

The SLP applied in Area 1 is changed in the range of ±50% to view the performance of the system under various load demand

Table 6
Optimal PID controller gains and system performance - collectively varying system parameters by +50%.

System parameters							
T_{H1} = 0.12 s		T_{T1} = 0.45 s		T_{r1} = 15 s		K_{r1} = 0.75	B_1 = 0.6375
Area 1			Area 2			System performance	
K_{p1}	T_{i1}	T_{d1}	K_{p2}	T_{i2}	T_{d2}	Settling time (s)	Max. overshoot (Hz)
2.0000	0.2000	0.8867	2.0000	0.2356	1.0065	4.9348 9.5116	−0.00234 −0.00272

Table 7
Optimal PID controller gains and system performance - collectively varying system parameters by +25%.

System parameters							
T_{H1} = 0.10 s		T_{T1} = 0.375 s		T_{r1} = 12.5 s		K_{r1} = 0.625	B_1 = 0.53125
Area 1			Area 2			System performance	
K_{p1}	T_{i1}	T_{d1}	K_{p2}	T_{i2}	T_{d2}	Settling time (s)	Max. overshoot (Hz)
2.0000	0.2000	0.9403	2.0000	0.2269	1.0861	7.9858 9.7697	−0.0025 −0.00258

Table 8
Optimal PID controller gains and system performance - collectively varying system parameters by -25%.

System parameters							
T_{H1} = 0.06 s		T_{T1} = 0.225 s		T_{r1} = 7.5 s		K_{r1} = 0.375	B_1 = 0.31875
Area 1			Area 2			System performance	
K_{p1}	T_{i1}	T_{d1}	K_{p2}	T_{i2}	T_{d2}	Settling time (s)	Max. overshoot (Hz)
2.0000	0.3530	1.7005	2.0000	0.2000	0.9975	8.8595 9.0126	−0.00463 −0.00273

Table 9
Optimal PID controller gains and system performance - collectively varying system parameters by -50%.

System parameters							
T_{H1} = 0.04 s		T_{T1} = 0.15 s		T_{r1} = 5 s		K_{r1} = 0.25	B_1 = 0.2125
Area 1			Area 2			System performance	
K_{p1}	T_{i1}	T_{d1}	K_{p2}	T_{i2}	T_{d2}	Settling time (s)	Max. overshoot (Hz)
2.0000	0.8183	1.4027	2.0000	0.2000	1.2301	10.0237 12.6195	−0.00588 −0.00239

(ΔP_L). The nominal load of the system is 0.01 pu MW and this value is maintained in Area 2. Referring to results in case I and case II, the weightage set is selected as $w_1 = 0.2$ and $w_2 = 0.8$. However the performance index based on LAE is still evaluated to display the merit of each weightage set. The PID controllers in both areas are tuned simultaneously and the transient response of the system is obtained as observed in Tables 3 and 4 and Figs. 14–16.

The frequency deviation step response in Area 1 changes according to the load demand. This can be seen in the frequency response when $\Delta P_L = -50\%$, the overshoot value is lower compared to frequency response when $\Delta P_L = +50\%$. The frequency deviation step response in Area 2 has minimal amount of changes as the load demand value is held constant at 0.1 pu MW. The tie line power indicates the direction of power flow. When the load demand in Area 1 is less compared to Area 2 (SLP in Area 1 is −50% and – 25%), the power transfer from Area 1 to Area 2 can be observed and vice versa.

3.4. Case IV – SLP in both areas by varying system parameters

In order to further evaluate the efficiency and robustness of the controller, investigation is carried out by varying the system parameters. In single objective optimization, the system parameters are varied separately to observe the effect of single parameter changes as investigated by [15]. The parameters changed are the hydraulic time constant (T_{H1}), steam turbine time constant (T_{T1}), reheat element time constant (T_{r1}), reheat gain (K_{r1}) and the frequency bias value (B_1). In this research, the system parameters in

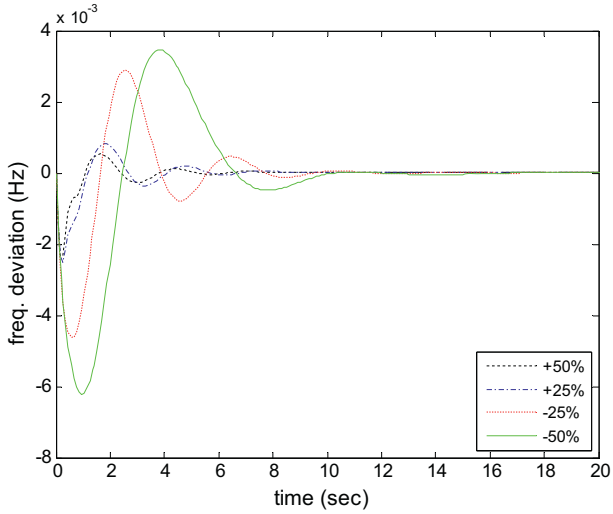

Fig. 17. Frequency deviations in Area 1 by collectively varying system parameters in the range of ±50%.

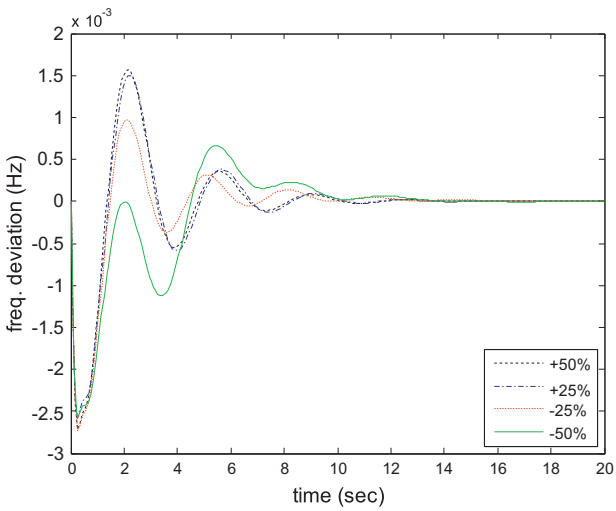

Fig. 18. Frequency deviations in Area 2 by collectively varying system parameters in the range of ±50%.

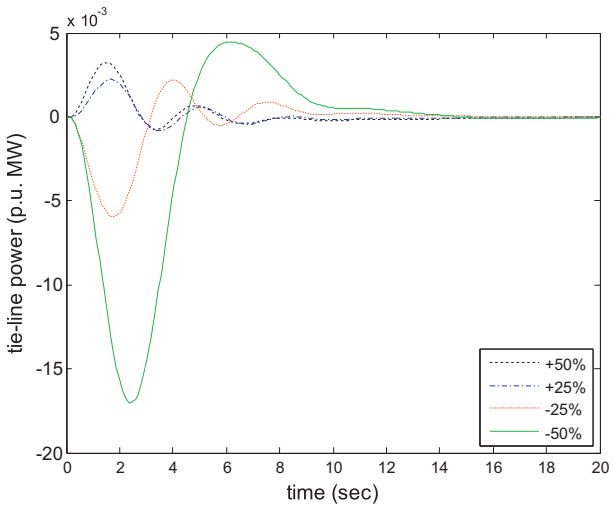

Fig. 19. Tie-line power changes by collectively varying system parameters in the range of ±50%.

Area 1 are changed collectively based on the given range while the nominal system parameters in Area 2 are maintained. The weightage set is selected as $w_1 = 0.2$ and $w_2 = 0.8$. SLP of 1% (0.01 pu MW) is applied for both areas simultaneously.

Varying the system parameters collectively for each area will result in a power system with unequal generation parameters. This will allow us to further test the robustness and efficiency of the proposed optimization technique compared to single parameter variation. The results are shown in Tables 5–9 and the step response are shown in Figs. 17–19. The results show the frequency response and tie line power corresponding to the collective variation of system parameters. The transient response of the system is within the permissible level. When the system parameters are varied in the range of −50%, large frequency excursion and tie line power deviation can be observed. This range represents an extreme condition in the system. The controller is still able to respond and rapidly settle the system oscillation albeit a greater maximum overshoot in tie line power is observed. Another important observation made is that for all the investigated cases, the proportional gain of the controller is optimally tuned to the maximum value of 2. Investigation further reveals that the maximum value for K_p gives the best response as shown in the results. With this information, in future we can fix the K_p value to simplify and hasten the controller optimization process.

4. Conclusion

In this paper a multiobjective optimization using the weighted sum approach is used to optimize the PID controller's parameters of the LFC. The nature inspired swarm intelligence ABC algorithm is modified and used to tune the PID parameters. The transient response of the system – frequency deviation step response and tie line power deviation is observed and the result of the system performance in terms of settling time and overshoot value are analyzed. The triple search capability of the ABC algorithm allows the global optimum points to be detected without being stuck in the local minima. The local exploitation of the fitness selection is enhanced by the global exploration of the algorithm which is represented by the random search process in the scout bee phase. In this research, both the settling time and maximum overshoot are given significant importance as functions to be minimized. The PID parameters for both the areas are updated simultaneously based on the ITAE and ITSE composite objective function discussed above. Analysis was carried out to determine the optimum weightage selection and a performance index based on LAE was formulated to evaluate the merit of each weightage set. Based on the investigation carried out, the weightage set of $w_1 = 0.2$ and $w_2 = 0.8$ is determined as the best selection. The weighted sum ABC tuned PID controller was also able to outperform the conventional PI and PID controller when comparatively investigated. In order to observe the effect of load demand on system performance, the SLP for one area is varied while the SLP for another area is maintained. The step response of the system corresponds accordingly to the value of load demand. The investigation is further extended by applying SLP in both areas while collectively varying the system parameters. The robustness of the method is proven when the system response and performance index is analyzed. The PID controllers in the investigation are tuned to provide optimum response in maximum overshoot and settling time. The ABC algorithm has proven to be effective in dealing with multiobjective optimization problem. This algorithm can be incorporated in further implementation of multiobjective optimization. In order to investigate the effect of weight in the multiobjective optimization problem, adaptive weighted sum method can be used. This would enable the algorithm to find the Pareto optimal solutions by

adaptively modifying the weight values in the composite objective function.

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Appendix A

The nominal parameters of the system investigated are:

f = 60 Hz.
T_{H1}, T_{H2} = 0.08 s.
T_{T1}, T_{T2} = 0.3 s.
T_{r1}, T_{r2} = 10 s.
T_{12} = 0.086 pu MW/rad.
T_{p1}, T_{p2} = 20 s.
K_{r1}, K_{r2} = 0.5.
K_{P1}, K_{P2} = 120 Hz/pu MW.
R_1, R_2 = 2.4 Hz/MW.
B_1, B_2 = 0.425 MW/Hz.

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