International Journal on
"Technical and Physical Problems of Engineering"
(IJTPE)
Published by International Organization of IOTPE

ISSN 2077-3528
IJTPE Journal
www.iotpe.com
ijtpe@iotpe.com

March 2013	Issue 14	Volume 5	Number 1	Pages 66-73

VEPSO BASED PID WITH LOW PASS FILTER FOR LFC DESIGN

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Abstract- This paper employs an adaptive Vector Evaluated Particle Swarm Optimization (VEPSO) algorithm to tune optimal gains of a Proportional Integral Derivative (PID) controller with low pass filter for Load Frequency Control (LFC) scheme in an interconnected power system that shift the system eigenvalues to the left of a vertical line in the s-plane. The problem of robustly tuning of practical PID based LFC design is formulated as an optimization problem according to the time domain-based objective function which is solved by the VEPSO technique that has a strong ability to find the most optimistic results. To demonstrate the effectiveness of the proposed method a two-area interconnected power system is considered as a test system under different operating conditions. The eigenvalue analysis and the nonlinear simulation results show the effectiveness of the proposed PID to damp out oscillations and work effectively over a wide range of loading conditions and system configurations.

Keywords: LFC, VEPSO, Practical PID, Power System Stability, Eigenvalue.

I. INTRODUCTION

Load Frequency Control (LFC) is one of the most importance issues in electric power system design and operation. The objective of the LFC in an interconnected power system is to maintain the frequency of each area and to keep tie-line power near to the scheduled values by adjusting the MW outputs the LFC generators so as to accommodate fluctuating load demands. The LFC problem has been dealt with extensively for more than four decades. A comprehensive literatures review about the earlier studied in the field of LFC problem has been presented by Shayeghi et. al [1].

Despite the potential of the modern control techniques with different structure, Proportional Integral Derivative (PID) type controller is still widely used for solution of the LFC problem [2-4]. This is because it performs well for a wide class of process. Also, they give robust performance for a wide range of operating conditions and easy to implement. The PID (PI) controller parameters tuning are usually done by trial and error methods based on the conventional experiences. Hence, they are not my capable of provide good robust performance for power system subjected to different kinds of uncertainties and disturbances. On the other hand, Goshal [2] have presented a comprehensive analysis of the effects of the different PID controller parameters on the overall dynamic performance of the LFC problem. It is shown that the appropriate selection of PID controller parameters results in satisfactory performance during system upsets. Thus, the optimal tuning of a PID gains is required to get the desired level of robust performance.

Recently, global optimization techniques like Genetic Algorithms (GA), Particle Swarm Optimization (PSO) and Simulated Annealing (SA) [5-7] have been applied for optimal tuning of PID based LFC schemes. These evolutionary algorithms are heuristic population-based search procedures that incorporate random variation and selection operators. Although, these methods seem to be good methods for the solution of PID parameter optimization problem, however, when the system has a highly epistatic objective function (i.e. where parameters being optimized are highly correlated), and number of parameters to be optimized is large, then they have degraded efficiency to obtain global optimum solution.

These meta-heuristic algorithms have some advantages and some disadvantages. In other hand, VEPSO Algorithm is a new meta-heuristic technique which is inspired from the sociological behavior associated with several bird flocking. In order to overcome these drawbacks, an VEPSO algorithm based PID type controller is proposed for the solution of the LFC problem in this paper. Here, the VEPSO optimization algorithm is used for the optimal tuning of the PID parameters to improve the optimization synthesis and damping of frequency oscillations.

The VEPSO algorithm is a typical swarm-based approach to optimization and has emerged as a useful tool for engineering optimization. It incorporates a flexible and well-balanced mechanism to adapt to the global and local exploration and exploitation abilities within a short computation time. Hence, this method is efficient in handling large and complex search spaces [8]. The effectiveness of the proposed controller is demonstrated through time domain simulation studies to damp frequency oscillations under different operating conditions and system nonlinearities. Results evaluation show that the VEPSO based tuned damping controller achieves good robust performance for a wide range of plant parameters changes even in the presence of

Generation Rate Constraints (GRC) and is superior to the designed controller using the PSO technique [9] and classical controllers [10].

II. PLANT MODEL

The power systems are usually large-scale systems with complex nonlinear dynamics. However, the major part of the work reported so far has been performed by considering linearized models of two/multi area power systems [1-3]. In advanced control strategies (such as the one considered in this paper) the error caused by simplification and linearization are considered as parametric uncertainties. A two-area power system is taken as test system in this study. Figure 1 shows the block diagram of the system in detail. The nomenclature used and the nominal parameter values are given in [6, 10].

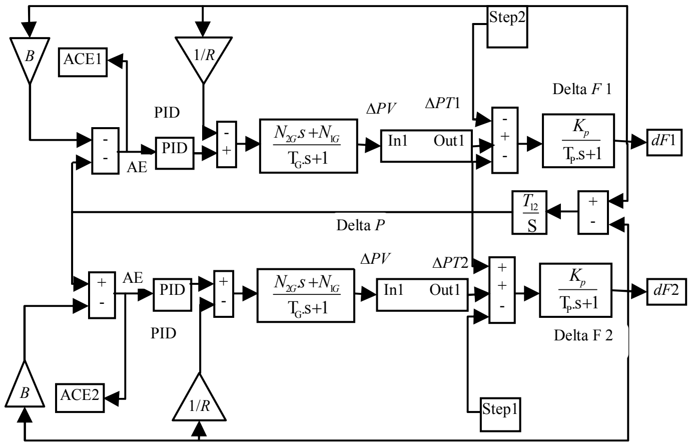


Figure 1. Block diagram of a two-area power system

It was shown that the Governor Dead-Band (GDB) nonlinearity tends to produce continuous oscillations in the area frequency and tie-line power transient response [11]. Figure 2 shows the nonlinear model of governor for consideration GDB. The governor dead-band effects that are important for speed control under small disturbance are considered to be 0.06% [12].

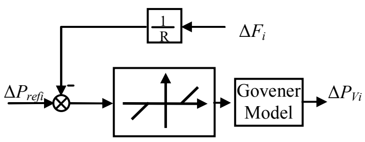


Figure 2. A nonlinear model of governor with GDB

One of the importance constraints in the LFC problem is GRC, i.e. practical limit on the rate of change in the generation power of each generator. The results in [10, 13] indicated that GRC would influence the dynamic responses of the system significantly and lead to larger overshot and longer settling time. In order to take effect of the GRC into account, the linear model of turbine $\Delta PV_i/\Delta PT_i$ in Figure 1 is usually replaced by a nonlinear model of Figure 3 (with $\pm\delta$ limit). Also, a limiter, bounded by $\pm\delta$ limit was used within the PID controller for governor system to prevent the excessive control action. In this study, δ is considered to be 0.015 [6].

For achieving LFC goals, i.e. frequency regulation and tracking the load demands, maintaining the tie-line power interchanges to specified values in the presence of modeling uncertainties, system nonlinearities and area load disturbances [1], a control signal made up of tie line power flow deviation added to frequency deviation weighted by a bias factor called ACE is used as the control signal in the LFC problem.

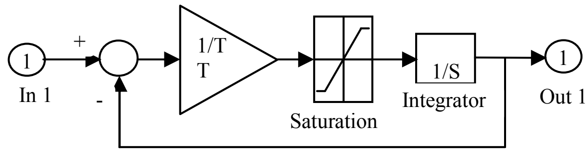


Figure 3. Nonlinear turbine model with GRC

By taking ACE_i as the system output, the PID controller transfer function in each control area over a given time interval s in Laplace domain is defined by, $(-G_i(s)ACE_i(s))$, where $G(s)$ is in:

$$G_i(s) = K_{Pi} + \frac{K_{Ii}}{s} + K_{Di}s \tag{1}$$

where, K_P is the proportional gain, K_I is the integral gain and K_D is the derivative gain. Generally, a low-pass filter is added to differential feedback loop serially to solve the noise problem and practical implementation as follows:

$$G_i(s) = K_{Pi} + \frac{K_{Ii}}{s} + \frac{K_{Di}s}{1+\tau_{Di}s} \tag{2}$$

where, $|\tau_{Di}| << 1$ and usually is considered $K_{Di}/100$.

III. VECTOR EVALUATED PARTICLE SWARM OPTIMIZATION

A. Brief Review of PSO Algorithm

The standard of the PSO are best describe as sociologically inspired, since the original algorithm was based on the sociological behavior associated with bird flocking [14]. PSO is simple in concept, few in parameters, and easy in implementation, besides it has an excellent optimization performance. At first, PSO was introduced for continuous search spaces and because of the aforementioned features, it has been widely applied to many optimization problems soon after its introduction [15]. To explain how PSO algorithm works, an optimization problem which requires optimization of N variables simultaneously is considered here. PSO is initialized with a population of solutions, called "particles".

At first, a random position and velocity is assigned to each particle. The position of each particle corresponds to a possible solution for the optimization problem. A fitness number is assigned to each particle which shows how good its position is. During the optimization process, each particle moves through the N-dimensional search space with a velocity that is dynamically adjusted according to its own and its companion's previous behavior. Updating the particle velocity is based on three terms, namely the "social," the "cognitive," and the "inertia" terms.

The "social" part is the term guiding the particle to the best position achieved by the whole swarm of particles so far (*gbest*), the "cognitive" part guides it to the best position achieved by itself so far (*pbest*), and the "inertia" part is the memory of its previous velocity ($\omega.v_n$). The following formulae demonstrate the updating process of a particle position (x_n) and its velocity (v_n) in the nth dimension in an N-dimensional optimization space [16]:

$$v_i^{k+1} = wv_i^k + c_1R_1\left(pbest_i^k - x_i^k\right) + c_2R_2\left(gbest^k - x_i^k\right) \quad (3)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (4)$$

where, R_1 and R_2 are random numbers uniformly distributed in range (0,1). The c_1 and c_2 are acceleration constants and ω is the inertia weight. These three parameters determine the tendency of the particles to the related terms.

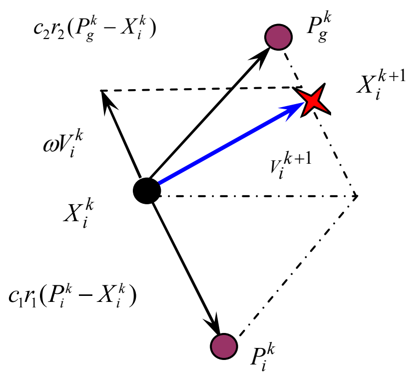


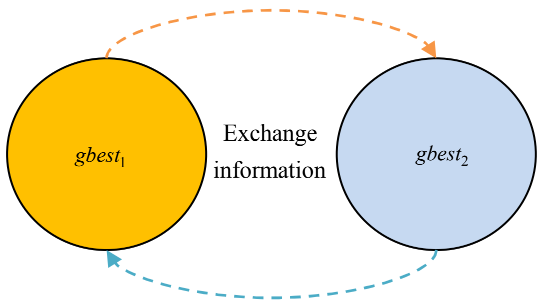
Figure 4. Velocity and location of particle updating process

Moreover, another parameter is used to limit the maximum velocity of a particle (V_{max}). All these parameters directly affect the optimization behavior; for example, the inertia weight controls the exploration ability of the process while the acceleration constants and maximum velocity are parameters for controlling the convergence rate [15, 16]. The iterative procedure of updating the velocities and positions of particles continues until the best position achieved by the whole swarm of particles (*gbest*) does not change over several iteration. Figure 4 shows this process obviously.

B. VEPSO

The vector evaluated approach can be classified as a criterion-based multi-objective strategy, where different stages of the optimization process consider different objectives [16, 17]. The actual implementation involves assigning each objective function to one of multiple populations for optimization. Information with respect to the different populations is exchanged in an algorithm-dependent fashion resulting in the simultaneous optimization of the various objective functions. As previously stated, the advantage of this approach lies in reduced computational complexity, which is a desirable property when solving a complex combinatorial problem where the fitness function evaluations are in them computationally expensive. The basic concept of VEPSO algorithm is illustrated in Figure 5.

As an example, for the case of two objective functions, X_1 and X_2 is swarm 1 and swarm 2, respectively, while $gbest_1$ and $gbest_2$ are the *gbest* for swarm 1 and swarm 2, respectively. As usual, v_1, v_2, s_1, and s_2 are the velocities and positions of each swarm. X_1 evaluates the objective function f_1 and X_2 evaluates the objective function f_2. There is no necessity for a complicated information migration scheme between the swarms as only two swarms are employed. Each swarm is exclusively evaluated according to the respective objective function. The *gbest* of the second swarm (X_2) is used for the calculation of the new velocities of the first swarm's (X_1) particles and accordingly, *gbest* of the first swarm (X_1) is used for the calculation of the new velocities of the second swarm (X_2). The VEPSO assumes that the search behavior of a swarm is affected by a neighboring swarm. The procedure of exchanging information among swarms can be clearly viewed as a *migration* scheme in a parallel computation framework. The flow chart is given as Figure 5.



$$v_1^{k+1} = w\,v_1^k + c_1.R_1.\left(pbest_1^k - x_1^k\right) + c_2.R_2.\left(gbest_2^k - x_1^k\right)$$

$$v_2^{k+1} = w\,v_2^k + c_1.R_1.\left(pbest_2^k - x_1^k\right) + c_2.R_2.\left(gbest_1^k - x_1^k\right)$$

Figure 5. The basic concept of VEPSO

IV. NON-DOMINATED SORT (NDS)

A Non-Dominated Sort (NDS) technique is applied for building the Pareto ranks that divide solutions into different fronts with different ranks. Thus, this technique is used to find multiple trade-off solutions in the optimization problem. The ranking of solutions is first done based on non-dominated sort, pursuance by fuzzification techniques. While non-dominance based rank drives the all agents towards Pareto optimal front, fuzzy mechanism based rank aims to preserve the diversity among solutions [18]. The ranking scheme is illustrated in Figure 6. In first sorting, each particle is chosen and checked whether it satisfies the rules given below with respect to any other agent in the population or not:

$$Obj.1[i] < Obj.1[j] \text{ and } Obj.2[i] < Obj.2[j] \text{ , } i \neq j \quad (5)$$

where, i and j are the agent numbers. After the rules are satisfied for any one of the remaining agent, the selected agent is then marked as dominated. Otherwise, the selected agent is marked as non-dominated. After ranking the whole population, a large fitness value is then assigned to the individuals in the first non-dominated front with rank 1. To maintain the goal of diversity, the sharing strategy is applied and the shared fitness of each individual in front 1 is obtained.

Then, a fitness value that is smaller than the minimum shared fitness value of the previous front is assigned to the individuals in the next front. Once again, the sharing strategy is used and the individual shared fitness values in the second front are obtained. The procedure is continued until the individual shared fitness values in all fronts are obtained. The sharing function values (share(d_{ij})) of all the first front agents can be calculated using:

$$\text{share}\left(d_{ij}\right)=\begin{cases}1-(\dfrac{d_{ij}}{\mu_{share}})^2, \text{if} \quad d_{ij}<\mu_{share} \\ 0 \qquad\qquad\qquad , \text{otherwise}\end{cases} \tag{6}$$

$$d_{ij}=\sqrt{\sum_{a=1}^{P_1}(\frac{x_s^i-x_s^j}{x_s^{\max}-x_s^{\min}})^2} \tag{7}$$

where, p_1 is the total number of decision variables, x_s is the value of sth decision variable, and i and j are the agent numbers. The μ_{share} is the maximum distance allowed between any two agents to become members of a niche, while the niche count for the total population (N) is calculated using the following formula:

$$Nichecount_i=\sum_{j=1}^{N}\text{share}\left(d_{ij}\right) \tag{8}$$

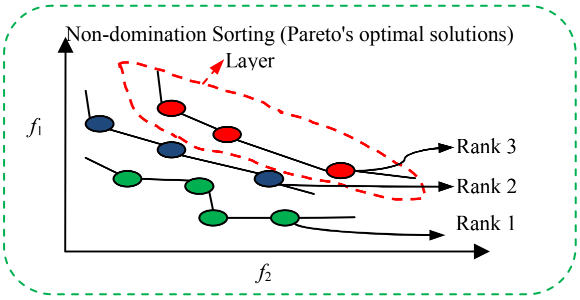


Figure 6. Non-dominated sorting mechanism (minimizing of f_1 and f_2)

V. BEST COMPROMISE SOLUTION

In the proposed VEPSO the fuzzy-based mechanism and fitness sharing are employed to aid the decision maker to choose the best compromise solution from the Pareto front. For practical applications we need to select one solution, which will satisfy the different goals to some extent. Usually, a membership function for each of the objective functions is defined by the experiences and intuitive knowledge of the decision maker. In this work, a simple linear membership function was considered for each of the objective functions. The membership function is defined as [19]:

$$\mu_i=\frac{f_i^{\max}-f_i}{f_i^{\max}-f_i^{\min}} \tag{9}$$

$$FDM_i=\begin{cases}0 & \mu_i\le 0 \\ \mu_i & 0<\mu_i<1 \\ 1 & \mu_i\ge 1\end{cases} \tag{10}$$

where $F_i^{\min}$ and $F_i^{\max}$ are the maximum and minimum values of the ith objective function, respectively. For each non-dominated solution k, the normalized membership function FDM^k is calculated as:

$$FDM^k=\left[\frac{\sum_{i=1}^{N_{obj}}FDM_i^k}{\sum_{j=1}^{M}\sum_{i=1}^{N_{obj}}FDM_i^j}\right] \tag{11}$$

where, M is the number of non-dominated solutions, and N_{obj} is the number of objective functions. Figure 7 illustrates a typical shape of the membership function.

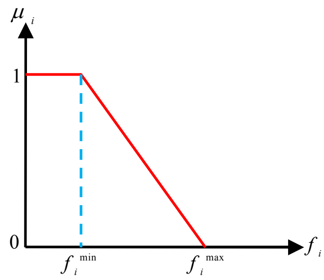


Figure 7. The membership function

VI. VEPSO BASED PID TYPE LFC

In this study, PID controller is used for the solution of LFC problem. This is because it used in almost all sectors of industry and science such as power systems, easy to implement and familiar to engineers [3, 6]. It should be noted that the transient performance of the power system with respect to the control of the frequency and tie-line power flows obviously depends on the optimal tuning of the PID controller's parameters. On the other hand, the conventional methods to tune PID gains not able to locate or identify the global optimum for achieving the desired level of system robust performance due to the complexity and multi-variable conditions of the power systems and also they may be tedious and time consuming. In order to overcome these drawbacks and provide optimal control performance, the VEPSO algorithm is proposed to optimal tune of PID gains under different operating conditions. Figure 8 shows the block diagram of VEPSO based tuned PID controller to solve the LFC problem for each control area (Figure 1).

The gains of PID controllers are tuned using VEPSO technique and then, the PID controller generates the control signal that applies to the governor set point in each area. In this study, the VEPSO module works offline. Simulation results show that the open loop system performance is affected more significantly by changing in the K_{pi}, T_{pi}, B_i and T_{ij} than changes of other parameters [17]. Thus, to illustrate the capability of the proposed strategy, in the view point of uncertainty our focus will be concentrated on variation of these parameters. It should be noted that choice of the properly objective function is very important in synthesis procedure for achieving the desired level of system robust performance. Because different objective functions promote different VEPSO behaviors, which generate fitness value providing a performance measure of the problem considered. For optimization problem, objective functions $ITAE$ based on ACE_i and FD based on system responses characteristic are defined as:

$$\begin{cases} J_1 = Max\left\{ITAE^{p=-\%30}, ITAE^{p=-\%20}, ..., ITAE^{p=+\%30}\right\} \\ ITAE^p = \sum_{i=1}^{N} \int_0^{10} (|ACE_1(t)| + |ACE_2(t)|)dt \end{cases} \quad (12)$$

where, t_{sim} is the time range of simulation; N is the number of area control in power systems and p is percent value of the uncertain plant parameters changes from the nominal values for which the optimization is carried out.

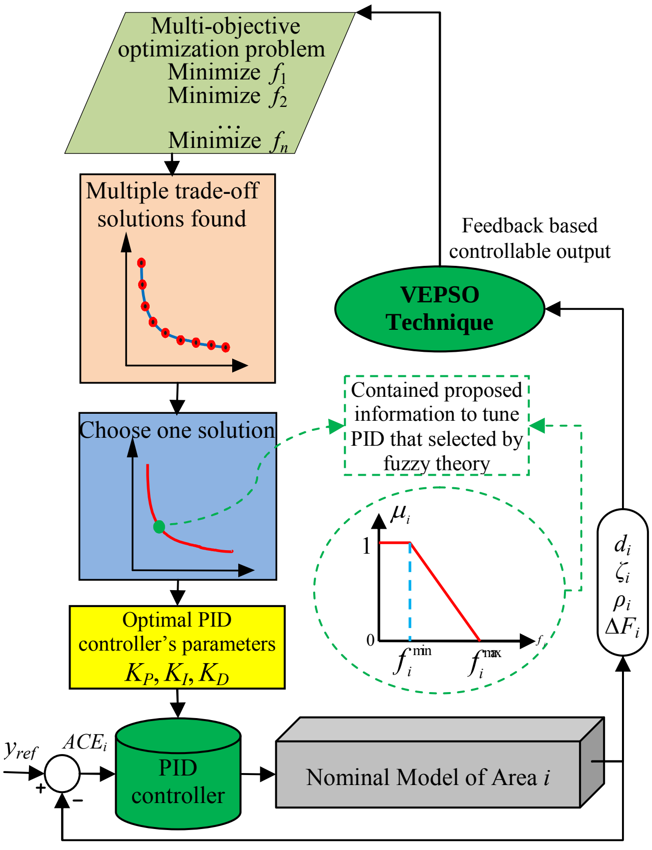


Figure 8. The proposed VEPSO based PID controller structure

It is aimed to minimize this objective function in order to improve the system response in terms of the settling time and overshoots. A power system can be modeled by a set of nonlinear differential equations as:

$$x = f(x,u) \quad \text{where,} \quad \dot{x} = Ax + Bu \quad (13)$$

where x is the vector of the state variables and u is the vector of input variables. The second objective function is eigenvalues based comprising the damping factor, and the damping ratio of the lightly damped electro-mechanical modes is defined as follows:

$$\begin{cases} J_2 = \max\left\{\text{eig}^{p=-\%30}, \text{eig}^{p=-\%20}, ..., \text{eig}^{p=+\%30}\right\} \\ \text{eig}_j = \sum_i (\sigma_0 - \sigma_i)^2 + \sum_i (\zeta_0 - \zeta_i)^2 \\ \text{if } \sigma_i \geq 0,\ \sigma_0 = 1.0,\ \text{if } \zeta_i > 0,\ \zeta_0 = 0.2 \end{cases} \quad (14)$$

where, σ_i and ζ_i are the real part and the damping ratio of the ith eigenvalue of the jth operating point. Also, all the closed loop system poles should lie within a D-shaped sector are shown in Figure 9.

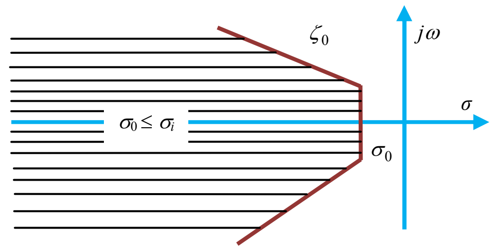


Figure 9. Region of eigenvalue location for the J_2 objective function

The design problem can be formulated as the following constrained optimization problem, where the constraints are the PID controller parameter bounds.

minimize J_1 and J_2 subject to

$$\begin{aligned} K_{Pi}^{\min} \leq K_{Pi} \leq K_{Pi}^{\max} \\ K_{Ii}^{\min} \leq K_{Ii} \leq K_{Ii}^{\max} \\ K_{Di}^{\min} \leq K_{Di} \leq K_{Di}^{\max} \end{aligned} \quad (15)$$

Typical ranges of the optimized parameters are [0.01-20]. To improve the overall system dynamical performance in a robust way and optimization synthesis, this paper employs VEPSO technique to solve the above optimization problem and search for optimal or near optimal set of PID controller parameters (K_{Pi}, K_{Ii} and K_{Di} for i=1, 2, …, N), which considers a multiple of operating conditions by applying a step load change 0.01 p.u. MW to one area. The operating conditions are considered with variation uncertain plant parameters of K_{pi}, T_{pi}, B_i and T_{ij} [20] from -30% to 30% of the nominal values by 10% step (i.e. 7 operating points). It should be noted that VEPSO algorithm is run several times and then optimal set of PID controller parameters is selected. The final values of the optimized parameters with two objective functions, J_1 and J_2, using the VEPSO and PSO techniques [6] are given in Table 1.

Table 1. Optimized parameters of PID controller

Algorithm	K_{p1}	K_{i1}	K_{d1}	K_{p2}	K_{i2}	K_{d2}
PSO	0.2066	0.3325	0.1119	0.0893	0.2954	0.4823
VEPSO	0.2828	0.4146	0.2345	0.7890	0.3563	0.3358

Figure 10 shows the relationship (tradeoff curve) of the J_1 and J_2 obtained by VEPSO. It is clearly shown that these solutions found were well-distributed and covered the entire Pareto front of case study. In addition, from the simulation results it is evident that if the operator wants to minimize J_1 and J_2 increases and vice versa.

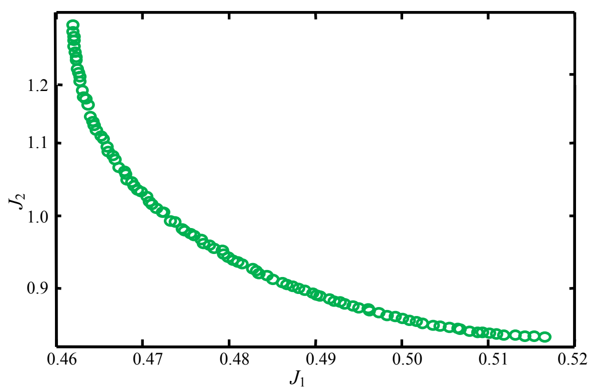


Figure 10. Pareto-optimal front of the proposed approach

VII. SIMULATION RESULTS

Figure 11 represents the simulation results for +30%, 0% and -30% change of parameters of LFC, respectively. The results of the proposed controller are compared with PSO PID] and classical PID controllers. The numerical results of *ITAE* and *FD* for case study are presented in Table 2. Moreover, the numerical result based performance indices are presented in Table 2. *ITAE* is calculated as:

$$ITAE = \int_{0}^{tsim} (|ACE_1(t)| + |ACE_2(t)|)dt \tag{16}$$

Actually the OS, US and T_s, are Overshoot (*OS*), Undershoot (*US*) and settling time which is considered in numerical results. The simulation results, represent the positive effect of VEPSO based PID controller on the improvement of the oscillation of frequency due to any load demands and disturbances. It can be seen that the proposed control strategy can be ensure the robust performance such for possible contracted scenario under modeling uncertainties in the various operating conditions. Table 2 shows the results of *ITAE* and other indices in different operating points for case study. It means that, overshoot, undershoot and settling time of frequency deviation are in appropriate situation in comparison of PSO.

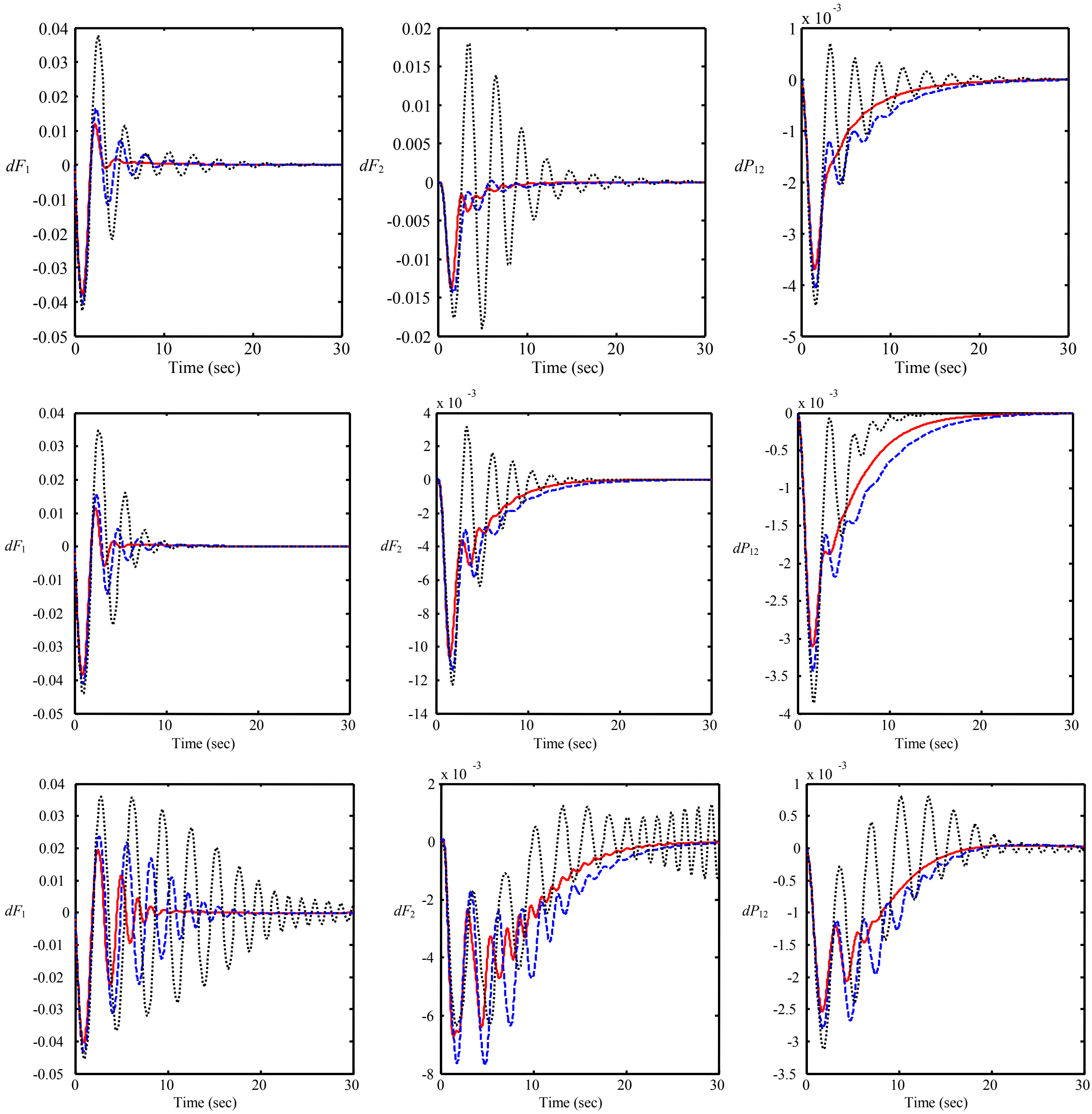


Figure 11. Deviation of frequency and tie lines power flows (+30%, 0%, -30% change of LFC); Solid (VEPSO),Dashed (PSO) and Doted (classical)

Table 2. Numerical performance indices

Index	*ITAE*			*US*			*OS*		
Change of parameters	Lead	PSO	VEPSO	Lead	PSO	VEPSO	Lead	PSO	VEPSO
30%	0.6791	0.2011	0.1020	0.0379	0.0164	0.0118	-0.0426	-0.0403	-0.0380
20%	0.3364	0.1751	0.0956	0.0354	0.0154	0.0111	-0.0424	-0.0405	-0.0381
10%	0.2338	0.1600	0.0916	0.0351	0.0149	0.0109	-0.0436	-0.0407	-0.0383
Nominal	0.2084	0.1519	0.0897	0.0347	0.0153	0.0114	-0.0438	-0.0410	-0.0385
-10%	0.2330	0.1499	0.0911	0.0346	0.0168	0.0129	-0.0446	-0.0415	-0.0389
-20%	0.3668	0.2011	0.1182	0.0351	0.0195	0.0154	-0.0453	-0.0423	-0.0395
-30%	1.2142	0.3893	0.1707	0.0359	0.0235	0.0193	-0.0456	-0.0432	-0.0404

Table 2. Numerical performance INDICES (continued)

Index	T_s			eigenvalue		
Change of parameters	Lead	PSO	VEPSO	Lead	PSO	VEPSO
30%	9.3631	5.5295	2.9032	-0.0032 ± 0.0398i -0.0110 ± 0.0267i	-0.0123 ± 0.0597i -0.0039 ± 0.0229i -0.0059 ± 0.0056i	-0.1908 ± 2.3218i -0.3787 ± 1.9087i
20%	11.3609	7.9555	2.9534	-0.0039 ± 0.0412i -0.0111 ± 0.0285i	-0.0130 ± 0.0619i -0.0044 ± 0.0242i -0.0068 ± 0.0048i	-0.3004 ± 2.5027i -0.5377 ± 2.1697i
10%	10.7865	7.5226	3.6766	-0.0044 ± 0.0428i -0.0111 ± 0.0306i	-0.0137 ± 0.0644i -0.0048 ± 0.0258i -0.0080 ± 0.0032i	-0.3901 ± 2.7583i -0.6292 ± 2.5235i
Nominal	11.2121	7.1272	3.7692	-0.0046 ± 0.0448i -0.0108 ± 0.0330i	-0.0143 ± 0.0669i -0.0050 ± 0.0279i	-0.4299 ± 3.0872i -0.6351 ± 2.9270i
-10%	12.9545	7.0796	3.8906	-0.0045 ± 0.0473i -0.0102 ± 0.0360i -0.0034 ± 0.0005i	-0.0146 ± 0.0695i -0.0146 - 0.0695i -0.0031 ± 0.0006i	-0.3994 ± 3.4807i -0.5631 ± 3.3675i -0.4088 ± 0.1893i
-20%	16.8750	9.0407	5.5311	-0.0038 ± 0.0503i -0.0090 ± 0.0397i -0.0027 ± 0.0012i	-0.0143 ± 0.0721i -0.0046 ± 0.0339i -0.0024 ± 0.0013i	-0.2815 ± 3.9374i -0.4075 ± 3.8537i -0.3133 ± 0.2359i
-30%	29.7289	14.871	7.7295	-0.0021 ± 0.0542i -0.0070 ± 0.0443i -0.0021 ± 0.0014i	-0.0126 ± 0.0746i -0.0035 ± 0.0382i -0.0019 ± 0.0015i	-0.0479 ± 4.4663i -0.1423 ± 4.4020i -0.2358 ± 0.2424i

VIII. CONCLUSIONS

In this paper, the adaptive Vector Evaluated Particle Swarm Optimization (VEPSO) algorithm has been successfully applied to the robust design of PID controllers for solution of the LFC problem. The design problem of the robustly selecting controller parameters is converted into an optimization problem according to time domain-based objective function over a wide range of operating conditions that is solved by a VEPSO technique which combines the advantages of PSO and some innovations for its self-adaptation. It has stronger global search ability and more robust than PSO and other heuristic methods. The effectiveness of the proposed strategy was tested on a two-area power system with various load changes in the presence of modeling uncertainties, GDB and GRC. Also, two different objective functions are proposed in this study for the LFC design problem. The first objective function is eigenvalues based comprising the damping factor, and the damping ratio of the lightly damped electromechanical modes, while the second is the time domain based multi-objective function. Compared with the PSO and conventional methods in term of *ITAE*, OS, eigenvalue and US, the simulation results show that the proposed VEPSO based tuned PID controller achieves good robust performance for a wide range of system parameters and is superior to PSO based tuned PID and other conventional controllers.

APPENDIX

System Data

$TT_1 = TT_2 = 0.3$ s, $TG_1 = TG_2 = 0.08$ s, $TP_1 = TP_2 = 20$ s

$R_1 = R_2 = 2.4$ Hz/puMW, $KP_1 = KP_2 = 120$ Hz/puMW

$T_{12} = 0.0866$ puMW/rad

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