Application of multi-objective PID controller for load frequency control in two-area nonlinear electric power systems

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Abstract: Design of optimal controllers is indeed a multi-objective optimisation problem. Non-dominated sorting in genetic algorithms-II (NSGA-II) is a popular algorithm for solving multi-objective optimisation problems. This paper investigates the application of NSGA-II technique for the tuning of a proportional-integral-derivative (PID) controller for a class of identical two area-thermal power stations including the generation rate constraint (GRC) and boiler nonlinear dynamics as well as the governor dead band (GDB). The design objective is to improve the damping of frequency fluctuation in two-area power system when subjected to a disturbance in their loads. The proposed technique is applied to generate Pareto set of global optimal solutions to the given multi-objective optimisation problem. Further, the two PID controllers in each area are assumed to have identical structures (same parameters). Simulation results using the tuned multi-objectives-based GA PID controller are presented. The effectiveness of the proposed scheme is confirmed using MATLAB-Simulink software.

Keywords: load frequency control; LFC; electric power system; PID controllers; multi-objective genetic algorithm; nonlinear systems.

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Biographical notes: Magdy A.S. Aboelela received his BSc and MSc degrees from Cairo University (Egypt) in 1977 and 1981. He received his PhD degree from the State University of Ghent, Belgium in 1989. He is currently working as a Professor at Cairo University. He has worked as a Visiting Professor at Ilorin University, Nigeria and Sultan Qaboos University in Oman. His interests are artificial intelligence, automatic control systems, stochastic modelling and simulation, decision support systems, management information systems, and application of computer technology in industry. He has published more than 70 scientific articles in journals and conference proceedings.

1 Introduction

Despite significant strides in the development of advanced control schemes over the past three decades, the classical proportional-integral-derivative (PID) controller and its variants remain the controllers of choice in many industrial applications (Bevrani et al., 2011; Khodabakhshian and Hooshmand, 2010). PID controller structure remains an engineer's preferred choice because of its structural simplicity, reliability, and the favourable ratio between performance and cost. Beyond these benefits, it also offers simplified dynamic modelling, lower user-skill requirements, and minimal development effort, which are issues of substantial importance to engineering practice. The performance of the PID controller depends on its setting of parameters. A lot of tuning methods have been presented in the literatures; these include designs based on guess-and check or trial and error tuning method, such as Ziegler-Nichols (Z-N) and Cohen-Coon methods (C-C). These conventional methods are hard to provide the desired performance and some fine tuning is further required. Design of an optimal PID controller requires optimisation of multiple performance measures that are often non-commensurable and competing with each other. Owing to multiple and conflicting objectives, an optimal PID controller that simultaneously minimises all objectives is usually not attainable. For example, while designing a control system, we would usually like to have a high-performance controller, but we also want to achieve desired performance with little control efforts (cost). One approach to design the optimal controllers is the classical weighted-sum approach where the objective function is formulated as a weighted sum of the objectives. But the problem lies in the correct selection of the weights to characterise the decision-makers preferences. In recent years, the multi-objective problems are solved to find non-inferior (Pareto-optimal, non-dominated) solutions (Deb, 2001). Control systems optimisation problems involving the optimisation of multiple objective functions require high computational time and effort (Carvalho et al., 1995; Liao and Li, 2002; Coello, 1999). As conventional techniques are difficult to apply, modern heuristic methods are preferred to obtain Pareto optimal set (Sivasubramani and Swarup, 2011; Cai et al., 2010; Panda, 2009).

Moreover, operation of power systems requires matching the total generation with the total load demand and with the associated system losses (Kundur, 1994). To achieve this goal, load frequency control (LFC) is introduced. In practice, LFC is one of the most important issues in power system design and operation for supplying sufficient and reliable electric power with good quality. The main objective of LFC is to control the real power output of generating units in response to changes in system frequency and tie-line power interchange within specified limits (Kothari and Nagrath, 2003).

With the increasing of complexity of modern power systems, applications of advanced control methods on the LFC problem have been reported in the last decade, e.g., optimal control (Ibraheem, 2004), adaptive control (Zribi et al., 2005), robust control (Tan and Xu, 2009; Tan, 2009), intelligent control (Cam, 2007), internal model control (Tan, 2010, 2011), predictive control (Liu et al., 2010), sliding-mode control (SMC) as a form of variable structure control (Utkin, 1992). A complete review of recent philosophies in LFC control strategies can be found in Shayeghi et al. (2009). Static Output Feedback gains and Linear Matrix Inequality are one of the most effective and efficient tool in control design, which can stabilise the system (Tripathy et al., 1984). The Robust adaptive control schemes have also been developed to deal with the changes in system parametric behaviour (Ghany, 2008). An intelligent controller such as PID-ANN, PI-fuzzy and optimal control applied to LFC have been reported in Stankovic (1998) and Parmar et al. (2010). Using genetic algorithm (GA) to scale the PI fuzzy controller in LFC has been reported in Chang and Fu (1997).

As far as power system models are concerned, a linear model around a nominal operating point is usually used in the LFC controller design. However, power system components are inherently nonlinear, so the implementation of LFC strategies based on a linearised model on an essentially nonlinear system does not necessarily ensure the stability of the system (Broujeni et al., 2011). As Tripathy et al. pointed out, the effects of these nonlinearities tend to produce continuous oscillations in the area frequency and tie-line power transient response (Vrdoljak et al., 2010). For the LFC problem, the nonlinearities of governor dead band (GDB) and generation rate constraint (GRC) are usually involved. A common technology to handle the nonlinearities is to design a controller for the linear nominal system; then, the linear model-based controller is directly imposed on the nonlinear system (Lu and Liu, 1995; Ramakrishna and Bhatti, 2008; Tripathy et al., 1992; Panda, 2009).

Nowadays, power system LFC complex problems are being solved with the use of evolutionary computation (EC) such as differential evolution (DE) (Rama Sudha et al., 2010), GAs, practical swarm optimisations (PSO) (Yousuf et al., 2010; Dorigo et al., 2007; Clere and Kennedy, 2002; Kennedy and Eberhart, 1995), and ant colony optimisation (ACO) (Bevrani, 2009). There are some of the heuristic techniques having immense capability of determining global optimum. Classical approach-based optimisation for controller gains is a trial and error method and extremely time consuming when several parameters have to be optimised simultaneously and provides suboptimal result. Some authors have applied GA to optimise controller gains more effectively and efficiently than the classical approach. Recent research has brought out some deficiencies in GA performance (Haupt, 2004; Whitley, 2005; Konak et al., 2006; Nanda et al., 2009). A more recent and powerful evolutionary computational technique 'bacterial foraging' (BF) is found to be user friendly and is adopted for simultaneous optimisation of several parameters (Passino, 2002; Srinivas and Deb, 1995).

The non-dominated sorting genetic algorithm (NSGA) proposed by Srinivas and Deb (Deb et al., 2002) has been widely used successfully to solve many multi-objective problems. However, the main demerit of this approach has been its high computational complexity, lack of elitism, and need for specifying a tunable parameter called sharing parameter. Deb et al. (2002) proposed an improved version of NSGA, called NSGA-II which has a better sorting algorithm, incorporates elitism and no sharing parameter need to be chosen a priori. By using of Pareto optimal set and Pareto optimal front which NSGA-II algorithm offers, designer can select the controller coefficients based on the priority of objectives.

In this study, multi-objective GA based on NSGA-II is used to determine the parameters of the PID controllers in two areas power system. Two similar PID controller gains (K_p, K_i and K_d) for each area have been proposed. A multi objective fitness function has been introduced to be minimised in the sense of NSGAII.

This paper is organised as follows: Section 2 introduces the NSGA-II algorithm. Section 3 explains the main components of the NSGA-II algorithm. In part 4, the application of the proposed methodology has been investigated for the nonlinear power system LFC problem. Section 5 shows the main conclusion of this paper.

2 Non-dominated shorting genetic algorithm-II

A multi-objective optimisation (MOO) problem differs from a single-objective optimisation problem because it contains several objectives that require optimisation. In case of single objective optimisation problems, the best single design solution is the goal. But for multi-objective problems, with several and possibly conflicting objectives, there is usually no single optimal solution.

Therefore, the decision maker is required to select a solution from a finite set by making compromises. A suitable solution should provide an acceptable performance over all objectives. There are two approaches to solve the MOO problems. One approach is the classical weighted-sum approach where the objective function is formulated as a weighted sum of the objectives. But the problem lies in the correct selection of the weights or utility functions to characterise the decision-makers preferences. In the second approach, a set of solutions called Pareto-optimal solution are generated and the decision is taken after the optimisation.

The ability to handle complex problems, involving features such as discontinuities, multimodality, disjoint feasible spaces and noisy function evaluations reinforces the potential effectiveness of GA in optimisation problems. Although, the conventional GA is also suited for some kinds of MOO problems, it is still difficult to solve those MOO problems in which the individual objective functions are in the conflict condition.

A generic single-objective GA can be easily modified to find a set of multiple non-dominated solutions in a single run. The ability of GA to simultaneously search different regions of a solution space makes it possible to find a diverse set of solutions for difficult problems with non-convex, discontinuous, and multi-modal solutions spaces. The crossover operator of GA exploits structures of good solutions with respect to different objectives to create new non-dominated solutions in unexplored parts of the Pareto front. In addition, most multi-objective approach does not require the user to prioritise, scale, or weigh objectives. Therefore, GA has been the most popular heuristic approach to multi-objective design and optimisation problems. Pareto-based fitness assignment was first proposed by Goldberg, the idea being to assign equal probability of reproduction to all non-dominated individuals in the population (Goldberg, 1989). The method consisted of assigning rank 1 to the non-dominated individuals and removing them from contention, then finding a new set of non-dominated individuals, ranked 2, and so forth. NSGA-II differs from a simple GA only in the way the selection operation is performed. The superiority of NSGA-II lies in the way multiple objectives are reduced to a single fitness measure by the creation of number of fronts, sorted according to non-domination.

Implementation of NSGA-II requires the determination of some fundamental issues. In the present paper, after initialising the population the following schemes are employed (Deb, 2001; Deb et al., 2002; Goldberg, 1989):

2.1 Non-dominated sorting

The initialised population is sorted based on non-domination using the following shorting algorithm.

- For each individual *I* in the main population *MP*, find the set of individuals *SI*, that is dominated by *i*.
- Find the number of individuals that dominate *I*, N_i.
- For each individual *j* in *MP*, if *I* dominates *j*, then add *j* to set *SI*. If *j* dominates *I*, increment the domination counter N_i for *i*.
- If no individuals dominate *I* then *I* belongs to the first front; set rank of individual *I* to 1, i.e., $i_{rank} = 1$. Update the first front set by adding *I* to front one.
- Repeat the above procedure for all the individuals *I* in main population *MP*.
- Initialise the front counter $f = 1$. For k^{th} non-empty front F_k, the set *S* for sorting the individuals at $(k + 1)^{\text{th}}$ front is done. For each individual *I* in F_k, and for each individual *j* in *SI*, domination count for individual *j* is decremented. If $N_j = 0$ then none of the individuals in the subsequent fronts would dominate *j*. Hence the rank of *j* is taken as $k + 1$ and the set *S* is updated with individual *j*.
- Increment the front counter and set *S* becomes the next front.

2.2 Crowding distance

The basic scheme behind the crowing distance calculation is the determination of Euclidian distance between each individual in a front based on their m objectives in the m dimensional space. All the individuals in the population are assigned a crowding distance value as the individuals are selected based on rank and crowding distance. Crowding distance is assigned front wise as below:

For each front F_k, *i* is the number of individual:

- For all the individuals initialise the distance to be zero. $F_k(d_j) = 0$, where *j* corresponds to the j^{th} individual in front F_k.
- For each objective function *m*, sort the individuals in front F_k based on objective *m*, $I = \text{sort}(f_k, m)$.
- Boundary values for each individual are assigned infinite value, $i_{d_1} = \infty$ and $i_{d_n} = \infty$. For $p = 2$ to $(n - 1)$.

$$I\left(d_p\right) = I\left(d_p\right) + \frac{I(p+1).\,m - I(p-1).m}{f_m^{\max} - f_m^{\min}} \tag{1}$$

where $I(p),m$ is the value of the m^{th} function of the p^{th} individual in *I*.

2.3 Selection and recombination

The selection is performed using a crowded comparison operator ac as below:

- Individuals in front F_k are ranked as $p_{rank} = i$.
- From the crowding distance $F_k(d_j)$, the ranks are compared using the comparison operator α_c i.e., p$\alpha_c q$ if $p_{rank} < q_{rank}$ or if p and q belong to the same front F_k then $F_k(d_p) > F_k(d_q)$.

By using tournament selection with crowed comparison-operator, the individuals are selected. Selection for individuals for next generation is performed by combining the current generation population and the offspring population. Elitism is ensured as all the previous and current best individuals are added in the population. Based on non-domination, population is sorted and the new generation is completed by each front subsequently until current population size is obtained

2.4 Genetic operators

2.4.1 Crossover

Simulated binary crossover scheme is employed in the present study which simulates the binary crossover observed in nature given as below:

$$\alpha_{1,k} = \left[(1-\gamma_k)\, p_{1,k} + (1+\gamma_k)\, p_{2,k}\right] / 2 \quad (2)$$

$$\alpha_{21,k} = \left[(1+\gamma_k)\, p_{1,k} + (1-\gamma_k)\, p_{2,k}\right] / 2 \quad (3)$$

where $\alpha_{i,k}$ is the i^{th} child with k^{th} component, $p_{i,k}$ the selected parent and α_k is the random generated sample (≥ 0) obtained from a uniformly sampled random number u between (0, 1) defined by:

$$p(\gamma) = \frac{\left[(\varepsilon_c + 1)\gamma^{\varepsilon_c}\right]}{2}, \quad \text{if } \leq \gamma \leq 1 \quad (4)$$

$$p(\gamma) = \frac{\left[(\varepsilon_c + 1)\gamma^{\varepsilon_c + 2}\right]}{2}, \quad \text{if } \gamma > 1 \quad (5)$$

$$\gamma(u) = (2u)^{\frac{1}{(\varepsilon+1)}} \quad (6)$$

$$\gamma(u) = 1 \Big/ \left[2(1-u)\right]^{\frac{1}{(\varepsilon+1)}} \quad (7)$$

where ε_c is distribution index for crossover.

2.4.2 Mutation

The polynomial mutation is employed in the presented study and can be defined as:

$$c_k = p_k + \left(p_k^u - p_k^l\right)\Delta k \quad (8)$$

where c_k is the child, p_k the parent and p_k^u and p_k^l are the upper and lower bounds on the parent components respectively. Δ_k is the small deviation calculated as below:

$$\Delta_k = (2r_n)^{\frac{1}{(\varepsilon_m+1)}} - 1, \quad \text{if } r_n < 0.5 \tag{9}$$

$$\Delta_k = 1 - \left[2(1-r_n)^{\frac{1}{(\varepsilon_m+1)}} - 1\right], \quad \text{if } r_n \geq 0.5 \tag{10}$$

where r_n is an uniformly sampled random number between (0, 1) and ε_m is mutation distribution factor.

3 Application to load frequency control

3.1 Application of NSGA-II

In the present study, after initialising the population the individuals in the populations are sorted based on non-domination into each front. The first front being completely non-dominant set in the current population and the second front being dominated by the individuals in the first front only and the front goes so on.

Each individual in the each front are assigned rank (fitness) values or based on front in which they belong to. Individuals in first front are given a fitness value of 1 and individuals in second are assigned fitness value as 2 and so on. In addition to fitness value a new parameter called crowding distance is calculated for each individual.

The crowding distance is a measure of how close an individual is to its neighbours. Large average crowding distance will result in better diversity in the population. Parents are selected from the population by using binary tournament selection based on the rank and crowding distance. An individual is selected in the rank is lesser than the other or if crowding distance is greater than the other.

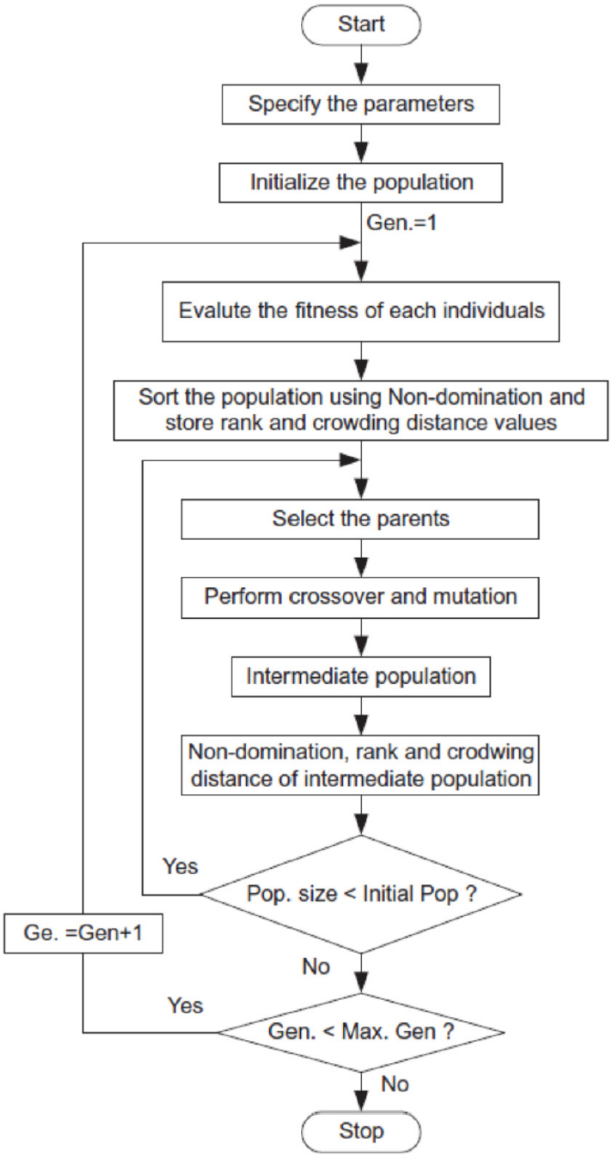
The selected population generates offspring from crossover and mutation operators, which will be discussed in detail in a later section. The population with the current population and current offspring is sorted again based on non-domination and only the best N individuals are selected, where N is the population size.

The selection is based on rank and the crowding distance of the last front. The objective function given in Eq. (16) is evaluated for each individual by simulating the system dynamic model. The population of NSGA-II is taken as 100 individuals (binary representation) and evolutionary cycle has stopping criterion of 100 generations. The flow chart of the NSGA-II algorithm used in this work is shown in Figure 1.

3.1.1 Best compromise solution

The notion of Pareto-optimality is only a first step towards solving a MOO problem. The choice of a suitable compromise solution from all non-inferior alternatives is not only problem dependent, it generally depends also on the subjective preferences of a decision agent, the decision maker. Thus, the final solution to the problem is the result of both an optimisation process and a decision process.

Figure 1 Flowchart of NSGA-II algorithm



The solution having the maximum value of l_i is the best compromise solution. The optimal controller parameters obtained by the above approach for the signals are given in Table 1.

Table 1 Two-area PID controller parameters using multi-objective GA and PSO technique

PID parameters	$K_{p1} = K_{p2}$	$K_{i1} = K_{i2}$	$K_{d1} = K_{d2}$
Multi objective GA values	4.9995	3.0106	4.9984
PSO values	3.8041	7.3970	9.9572

3.2 Multi-objective function

In many real-life problems, objectives under consideration conflict with each other, and optimising a particular solution with respect to a single objective can result in unacceptable results with respect to the other objectives (Liao and Li, 2002).

A reasonable solution to a multi-objective problem is to investigate a set of solutions, each of which satisfies the objectives at an acceptable level without being dominated by any other solution (Coello, 1999).

Being a population-based approach, GA are well suited to solve MOO problems. A generic single-objective GA can be modified to find a set of multiple non-dominated solutions in a single run. The ability of GA to simultaneously search different regions of a solution space makes it possible to find a diverse set of solutions for difficult problems with non-convex, discontinuous and multi-modal solutions spaces. The cross over operator of GA may exploit structures of good solutions with respect to different objectives to create new non-dominated solutions (Liao and Li, 2002).

The goal of MOO is to find as many of these solutions as possible. If reallocation of resources cannot improve one cost without raising another cost, then the solution is Pareto optimal. A Pareto GA returns a population with many members on the Pareto front. The population is ordered based on dominance.

Several different algorithms have been proposed and successfully applied to various problems such as (Coello, 1999): vector-evaluated GA (VEGA), multi-objective GA (MOGA), a non-dominated sorting GA (NSGA) and non-dominated sorting GA (NSGA II) which is used in the proposed research.

4 Nonlinear load frequency control model

Non-reheat type nonlinear two areas electric power system represented by a block diagram of a closed loop controlled system model is shown in Figure 2 for two-area electric power system, where f_i is the area's frequency (Hz), R_i is regulation constant (Hz/unit), T_{gi} is speed governor time constant (sec), T_{ti} is turbine time constant (sec), H_i is inertia constant (s) and D_i is area parameter (Mw/Hz) where $i = 1,2$.

The model includes the effect of GRC and limits on the position of the governor valve, which are caused by the mechanical and thermodynamic constraints in practical steam turbines systems.

A typical value of 0.01 p.u./min has been included in the model as stated in Cai et al. (2010).

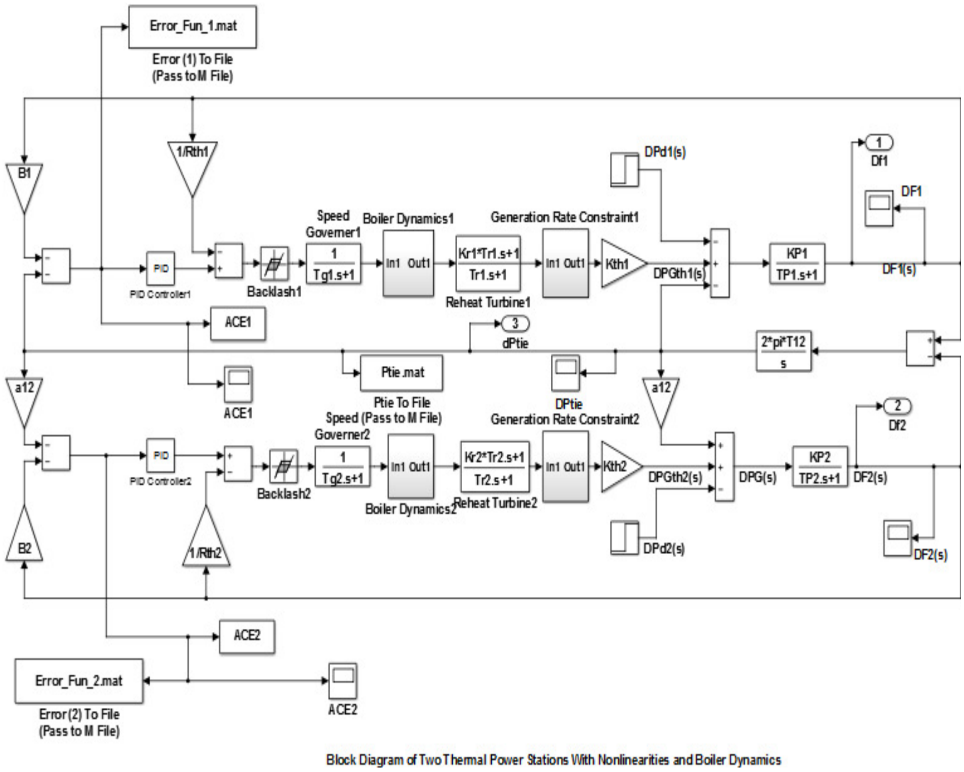
Area control error (ACE) signal is used as the plant output of each power generating area. Driving ACEs in all areas to zeros will result in zeros for all frequency and tie-line power errors in the system. So it can be defined as:

$$ACE_i = \sum_{i=1,\dots,n,\, j\neq i} \Delta P_{tie,ij} + b_i \Delta f_i \tag{11}$$

where B_i is the frequency response characteristic for area i:

$$b_i = D_i + \frac{1}{R_i} \tag{12}$$

Figure 2 Nonlinear two-area power system Simulink model with multi-objective GA-tuned PID controller



Percentage of overshoot and settling time are two more objective functions have been added to the objective function to define the multi-objective GA problem as explained later. The PID controllers in both the areas were considered to be identical. The control signal for the conventional PID controller can be given in the following equation:

$$U_i(s) = -G_{c_i}(s) \times ACE_i(s) \tag{13}$$

$$U_i(s) = -\left(K_p + \frac{K_i}{s} + K_d s\right)\left(\Delta P_{tie} + b_i \Delta f_i\right) \tag{14}$$

Now a performance indices can be defined as J_1, J_2 and J_3 as given below

$$\begin{aligned} J_1 &= \int_0^\infty \left|ACE_1\right| dt + \int_0^\infty \left|ACE_2\right| dt \\ J_2 &= Maximum\ P.O.\left(\Delta f_1\right) + Maximum\ P.O.\left(\Delta f_2\right) + Maximum\ P.O.\left(\Delta P_{tie}\right) \\ J_3 &= Settling\ Time\left(\Delta f_1\right) + Settling\ Time\left(\Delta f_2\right) + Settling\ Time\left(\Delta P_{tie}\right) \end{aligned} \tag{15}$$

where $P.O.$ stands for the percentage overshoot. Based on these performance indices J_1, J_2, and J_3 the optimisation problem can be stated as:

$$\textit{Minimize}\ \Im(j_1, j_2, j_3)$$

Subjected to:

$$\begin{aligned} &K_{p,l}^{\min} \le K_{p,l} \le K_{p,l}^{\max} \\ &K_{i,l}^{\min} \le K_{i,l} \le K_{i,l}^{\max} \\ &K_{d,l}^{\min} \le K_{d,l} \le K_{d,l}^{\max} \end{aligned} \tag{16}$$

where $K_{p,l}$, $K_{i,l}$, $K_{d,l}$ are the controller's parameters of the l^{th} area.

4.1 Best compromise solution

The notion of Pareto-optimality is only a first step towards solving a MOO problem. The choice of a suitable compromise solution from all non-inferior alternatives is not only problem dependent, it generally depends also on the subjective preferences of a decision agent, the decision maker. Thus, the final solution to the problem is the result of both an optimisation process and a decision process. In order to choose the optimal controller parameter among the Pareto optimal set, a Fuzzy-based approach is employed in the present paper. The j^{th} objective function of a solution in a Pareto optimal set j_j is represented by a membership function μ_j defined as (Panda, 2009):

$$\mu_j = \begin{Bmatrix} 1, & j_l \ll j_l^{\min} \\ \dfrac{j_l^{\max} - j_l}{j_l^{\max} - j_l^{\min}}, & j_l^{\min} < j_l < j_l^{\max} \\ 0, & j_l \gg j_l^{\max} \end{Bmatrix} \tag{17}$$

where $j_l^{\max}$ and $j_l^{\min}$ are the maximum and minimum values of the l^{th} objective function j_j for $l = 1,2$, and $n = 3$.

For each solution i, the membership function μ^i is calculated as

$$\mu^i = \frac{\sum_{j=1}^{n} \mu_j^i}{\sum_{i=1}^{m} \sum_{j=1}^{n} \mu_j^i} \tag{18}$$

where n is the number of objectives functions and m is the number of solutions. The solution having the maximum value of μ^i is the best compromise solution (Panda, 2009).

4.2 Simulation results

To simplify the study, the two interconnected areas were considered identical. So the optimal parameter chosen such that $G_{c1} = G_{c2} = G_c$ and $B_1 = B_2 = B$. The Pareto front technique has been applied to select the minimum optimal value of the performance index defined in equation (16) as explained before (Cam, 2007). In the simulation, the GA runs for 25 generations with a population size of 100. The other particle swarm parameters are given as:

- c0 (percentage of old velocity) = 0.65
- c1 (percentage towards global optimum) = 2
- c2 (percentage towards local optimum) = 2
- x0range (range of uniform initial distribution of positions) = [0 10]
- vstddev (std. deviation of initial velocities) = 1.

The parameters of the NSGA-II algorithm used in this work is given as:

- population size = 100
- elite count = 30
- number of generations = 100
- crossover and mutation probabilities were chosen as 0.9 and 0.01 respectively.

The nominal system parameters are:

- *First area*

  Tg1 = 0.08; Kr1 = 0.5; Tr1 = 10; KP1 = 120; TP1 = 20; T12 = 0.086; Rth1 = 2.4; Kth1 = 1; B1 = 0.425

- *First area*

  Tg2 = 0.08; Kr2 = 0.5; Tr2 = 10; KP2 = 120; TP2 = 20; T12 = 0.086; Rth2 = 2.4; Kth2 = 1; B2 = 0.425

- *First boiler*

  K1 = 0.85; K2 = 0.095; K3 = 0.92; Cb1 = 200; Td1 = 0.1; Krb1 = 0.03; Tib1 = 26; Trb1 = 69; TF1 = 10

- *Second boiler*

  K1 = 0.85; K2 = 0.095; K3 = 0.92; Cb2 = 200; Td2 = 0.1; Krb2 = 0.03; Tib2 = 26; Trb2 = 69; TF2 = 10

- *GRC of area one*

  Tt1 = 0.3; Saturation limit [0.1: –0.1]

- *GRC of area two*

  Tt1 = 0.3; saturation limit [0.1: –0.1]

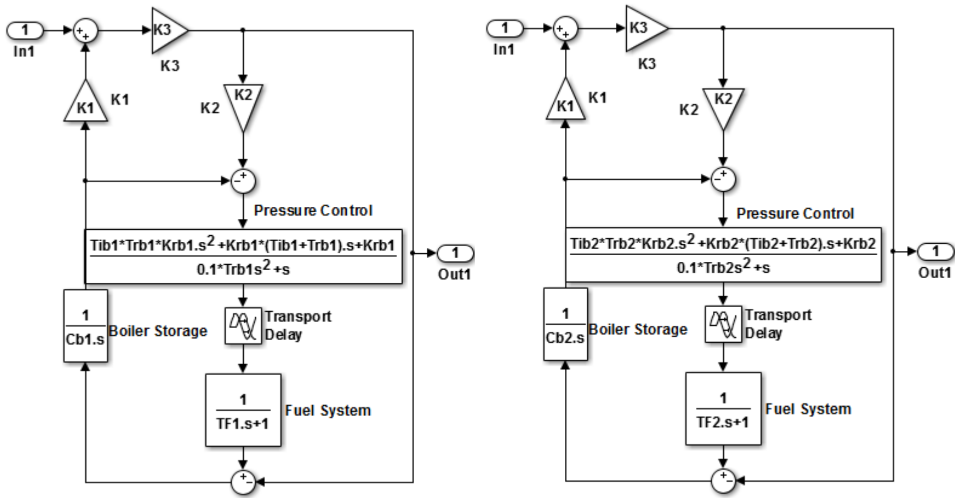
- *Generator dead band of area one*

  band width = 0.0001

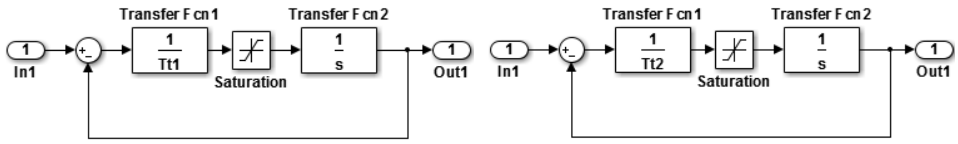
- *Generator dead band of area two*

  band width = 0.0001.

Figure 3 (a) Boiler dynamics model of area one (b) Boiler dynamics model of area two (c) GRC of area one (d) GRC of area two

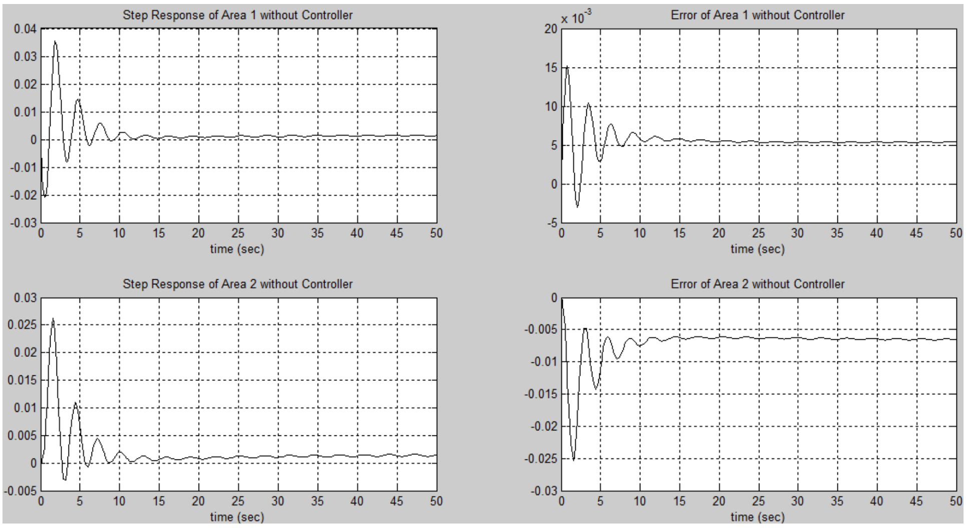


(a) (b)



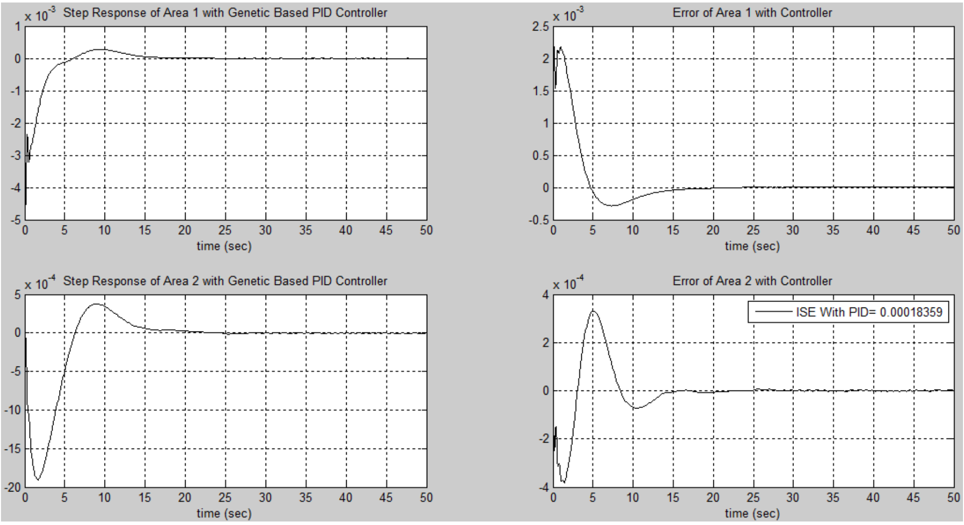
(c) (d)

Figure 4 (a) Frequency and ACE changes of the two areas after disturbance without controller (b) Frequency and ACE changes of the two areas after disturbance with multi-objectives GA-based PID controller (c) Frequency and ACE changes of the two areas after disturbance with PSO-based PID controller

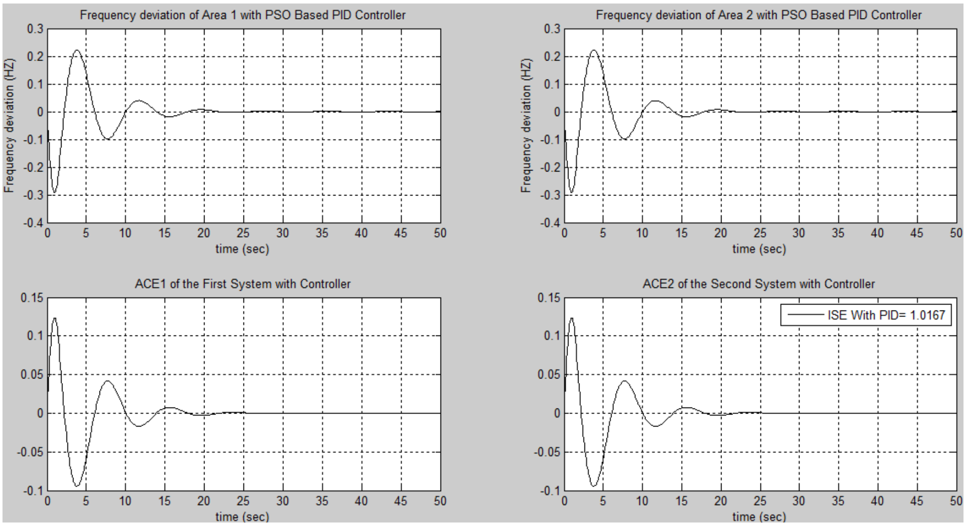


(a)

Figure 4 (a) Frequency and ACE changes of the two areas after disturbance without controller (b) Frequency and ACE changes of the two areas after disturbance with multi-objectives GA-based PID controller (c) Frequency and ACE changes of the two areas after disturbance with PSO-based PID controller (continued)



(b)



(c)

By using the Simulink model shown in Figures 2 and 3(a), 3(b), 3(c), as well as 3(d) in conjunction with equations (4)–(7), optimal controller parameters were obtained with multi-objective GA technique as shown in Table 1. We assume in this case that the two PID controllers are similar in parameters, i.e., $K_{i_1} = K_{i_2}$ and $K_{d_1} = K_{d_2}$. This condition can be released in other circumstance by considering two different PID controller's parameters. This will add a little computational effort to the algorithm but in general it is acceptable (less than a minute). The deal with different PID structures in the two areas is not a difficult task and can be done with the same steps mentioned in this article.

Figure 4(a) show the time domain performance of the frequency deviation in first area, second area and ACE index in both areas without controller. The great oscillation behaviour of the three curves is noticeable together with non-zero steady state value.

On the other hand, Figure 4(b) illustrates the frequency deviation in first area, second area and ACE index in both areas under the proposed multi-objective GA PID controller with step change of 0.01 p.u. in area 1 and zero in area 2 (Tammam et al., 2012a, 2012b, 2012c). A small percentage overshoot and a settling time is obtained in this case which is an advantage of applying this optimisation technique in getting the values of the PID controller's three parameters.

Moreover, Figure 4(c) delineates the behaviour of the PID controller based on the particle swarm optimisation (PSO) technique with similar loading conditions in order to compare the results with Figure 4(b) of the multi-objective GA. The overshoots of the frequency changes in the two areas in case of applying the proposed method is higher than those of the proposed multi-objective GA. One more fact about the performance of the two methods: the proposed multi-objective GA and the PSO method, the ISE error criterion in case of the first method is much lower than the second PSO algorithm (Tammam et al., 2012a, 2012b, 2012c). The ISE error criterion is defined as:

- *Area 1 integral of squared error for area 1 (ISE):*

$$ISE_1 = \int_0^\infty ACE_1^2(t)dt \tag{19}$$

- *Area 2 integral of squared error for area 2 (ISE):*

$$ISE_2 = \int_0^\infty ACE_2^2(t)dt \tag{20}$$

- *P_{tie} ISE (integral of squared error for tie line):*

$$ISE_{Ptie} = \int_0^\infty dp_{tie}^2(t)dt \tag{21}$$

where ACE_1, ACE_2 and dp_{tie} are the area 1 and area 2 control error as well as the change in the tie-power between the two areas (Tammam et al., 2012a, 2012b, 2012c). The minimum of this index, the better performance of the controller is.

Table 2 Response characteristics using multi-objective GA-tuned PID technique for two-area

	Overshoot	*Settling time (sec)*
Multi-objective GA-tuned PID technique		
First area frequency (Hz)	2.8276e-04	13.6317
Second area frequency (Hz)	3.7764e-04	16.0556
Tie line power (p.u)	2.4532e-04	14.1005
PSO tuned PID technique		
First area frequency (Hz)	0.2229	20.3678
Second area frequency (Hz)	0.2229	20.3678

5 Conclusions

In this proposed study, a non-dominated sorting multi-objective GA-based PID tuning technique has been investigated for automatic LFC of a nonlinear two-area electric power system.

For this purpose, a PID controller has been proposed for each area. The PID's gains: K_p, K_i and K_d of each area have been calculated and compared with the results of PSO technique.

It has been shown that the proposed control algorithm is effective and provides significant improvement in system performance.

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