APPLYING PARTICLE SWARM OPTIMIZATION TO DESIGN ADAPTIVE FUZZY LOGIC LOAD-FREQUENCY CONTROLLERS FOR A LARGE-SCALE POWER SYSTEM

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Abstract: Due to the continually time-by-time load variation, the working frequency and tie-line power flow in a large-scale power system will be deviated from their scheduled values. The most important objective of the Load-Frequency Control (LFC) strategy is to damp the oscillations of the frequency and tie-line power deviations to restore rapidly the steady state of the system. This paper focuses on designing a type of adaptive PI-based fuzzy logic (FL) load-frequency controllers, which can deal with the LFC problem in a complicated power system in reality. Scaling factors of such controller, which significantly impact on the control quality, will be optimized by applying the Particle Swarm Optimization (PSO) technique. Inspired by the biological evolutionary theory, the PSO method has been used successfully in many modern control schemes due to its great simplicity and efficiency. Hence, the proposed PSO-PI-based FL controllers can achieve the desired control properties when solving the LFC problem. Promising simulation results obtained in a typical test system can be used to validate the feasibility and superiority of the proposed control strategy in comparison with those of the conventional regulators using PID.

Key words: PSO, LFC, PI-type FL, frequency, tie-line power, deviation.

Nomenclature

i	index of the ith control-area, i = 1, 2, …, n
f_i	real frequency, Hz
f_n	nominal frequency, f_n = 50Hz
Δf_i	change of frequency, p.u.
$\Delta P_{D,i}$	load increment, p.u.
$T_{G,i}$	time constant of governor, s
$T_{T,i}$	time constant of non-reheat turbine, s
M_i	generator inertia constant, p.u.
D_i	load damping factor, p.u. MW/Hz
T_{ij}	tie-line time constant, s
$P_{tie,i}$	tie line power flow, p.u.
$\Delta P_{tie,i}$	deviation of tie line power flow, p.u.
B_i	frequency bias factor, MW/p.u. Hz
R_i	speed regulation, Hz/MW
ACE_i	Area Control Error

1. Introduction

In a large-scale multi-control-area interconnected power system, Load Frequency Control (LFC) or Automatic Generation Control (AGC) plays a crucial role to ensure the stability and economy of the network [1-3]. The main objective of the LFC is to extinguish the oscillations of both the system frequency and tie-line power flow resulting from continual load variations in an electric power grid. The working frequency and tie-line power deviated from the scheduled values need to be controlled efficiently enough to bring the steady state back to the system as quickly as possible after the load variation appearance.

To deal with the LFC problem, most of control strategies have been based on the tie-line bias theory [1]. According to this control method, Area Control Error (ACE) signal, a proportional combination of both the frequency and tie-line power deviations, can be used as the input of controllers. As a result, the damping of such two deviations can be obtained by regulating to minimize the ACE signal.

Based on the tie-line bias control strategy, many categories of load-frequency controllers have been designed recently [1-5]. Due to the inherent nonlinearity of a large-scale power system in reality, conventional regulators, such as Integral (I), Proportional-Integral (PI) and Proportional-Integral-Derivative (PID), should be replaced with the improved controllers using modern theory, e.g. fuzzy logic (FL). The most dominant advantage of the FL controllers is that they can implement efficiently to obtain the desirable quality even the control plant has several uncertain parameters [6]. Furthermore, the simple structure and implementation of such controllers are the other strengths to enhance their widespread application in practice.

When applying a FL-based load-frequency controller, however, there have been several factors which need to be tuned to obtain the desired control characteristics. For instance, the most efficient category of the FL controllers, namely PI-type FL controller, using two inputs (error and its derivative)

and one output, has three corresponding scaling factors which will affect significantly the control quality of the system. Therefore, it is highly necessary to apply a proper tuning method for such three scaling factors in order to design a robust adaptive FL controller which can solve efficiently the LFC problem in reality.

In this paper, the Particle Swarm Optimization (PSO) technique will be applied to deal with the above tuning issue. As an evolutionary computation method, the PSO algorithm inspired by the social behavior of creature swarms, such as fish and birds, has a flexible and well-balanced mechanism to enhance the global and local search capability [7-10]. Moreover, due to its simple implementation and high efficiency, the PSO technique has been used widely in many control problems, including the design of an adaptive FL controller. Three scaling factors of a PI-type FL controller will be optimized by using the PSO mechanism to achieve the optimal values. Thereafter, they can be used to adapt to a practically complicated multi-area interconnected power system. A typical test system of three-control-area non-reheat electric power grid with various load variation conditions will be investigated to verify the robustness of the proposed control strategy. Numerical simulation process using Matlab/Simulink package will also be implemented for both the proposed PSO-PI-based FL controllers and PID regulators. As a result, the feasibility and superiority of the proposed control scheme can be obtained when solving the problem of the LFC.

2. Dynamic plant model based on tie-line bias control strategy

According to the tie-line bias control strategy, both deviations of the system frequency and tie-line power flow can be minimized efficiently by using the definition of ACE signal. In principle, this signal is a proportional combination of such two deviations as expressed below [1]:

$$ACE_i(t) = \Delta P_{tie,i}(t) + B_i.\Delta f_i(t) \qquad (1)$$

where, $\Delta P_{tie,i}(t)$, $\Delta f_i(t)$ and B_i denote the tie-line power flow deviation, the system frequency change and the bias factor for the generating station #*i*, respectively.

Assuming that each generating station is simply composed of three equivalent components, namely, governor, turbine and generator units. Such a station is conceptually defined as a control-area which is normally interconnected directly or indirectly with others in a large-scale electric power grid. The structure of the *i*[th] control-area is described in Fig. 1. Here, frequency and power sensors are employed to collect the data of the network frequency and tie-line power deviations, respectively. According to the aforementioned analyses, the oscillations of these deviations resulting from the load variations need to be damped quickly enough to recover the stability of the network.
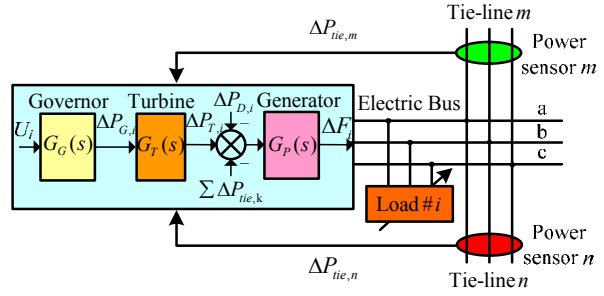

Fig. 1. The structure of the *i*[th] control-area

Table 1: Transfer functions of three main units

Main unit	Transfer function
Governor	$G_G(s) = \dfrac{1}{s.T_{G,i} + 1}$
Non-reheat turbine	$G_T(s) = \dfrac{1}{s.T_{T,i} + 1}$
Generator-load	$G_P(s) = \dfrac{1}{s.M_i + D_i}$

In the context of this work, in order to apply the adaptive control strategy for the LFC, a non-reheat *n*-control-area interconnected power system is chosen as a typical case study. The other categories of the control plants (e.g. hydro power network) can be modeled in a same manner. To design a dynamic model for the above non-reheat power system, three transfer functions of three main units mentioned above can be represented in Table 1. From Fig. 1, the open loop transfer function of the control plant without the consideration of the load and tie-line power flow can be given as follows:

$$\begin{aligned} G_{Open}(s) &= G_G(s).G_T(s).G_P(s) \\ &= \frac{1}{(sT_{G,i}+1)(sT_{T,i}+1)(sM_i+D_i)}. \end{aligned} \qquad (2)$$

While the load variation can be considered as a type of disturbance of the control system, the tie-line power deviation seems to be a feedback signal which is calculated as

$$\Delta P_{tie,i}(s) = 2\pi \sum_{j=1, j\neq i}^{n} \frac{1}{s} T_{ij} \left[\Delta F_i(s) - \Delta F_j(s) \right] \quad (3)$$

where T_{ij} is the synchronizing coefficient (tie-line time constant) between the area #*i* and area #*j*. After completing some simple transformations, the state-space model of the whole system can be obtained as:

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + FD \\ y(t) = C.x(t) \end{cases} \qquad (4)$$

where,

x(t) is the state variable vector

$$x(t) = \left[x_1(t), x_2(t), x_3(t), x_4(t) \right]^T \quad (5)$$

$$\begin{cases} x_1(t) = \left[\Delta f_1(t), ... \Delta f_i(t), ... \Delta f_n(t) \right]^T \\ x_2(t) = \left[\Delta P_{T,1}(t), ... \Delta P_{T,i}(t), ... \Delta P_{T,n}(t) \right]^T \\ x_3(t) = \left[\Delta P_{G,1}(t), ... \Delta P_{G,i}(t), ... \Delta P_{G,n}(t) \right]^T \\ x_4(t) = \left[\Delta P_{tie,1}(t), ... \Delta P_{tie,i}(t), ... \Delta P_{tie,n}(t) \right]^T \end{cases} \quad (6)$$

u(t) is the input signal vector,

$$u(t) = \left[u_1(t), ... u_i(t), ... u_n(t) \right]^T \quad (7)$$

D is the load variation vector,

$$D = \left[\Delta P_{D,1}(t), ... \Delta P_{D,2}(t), ... \Delta P_{D,n}(t) \right]^T \quad (8)$$

A, *B*, and *F* are the matrices of state, input, and load disturbance, respectively. The dynamic model built in (4) will be applied in the proposed LFC strategy using an efficient combination of fuzzy logic technique and PSO algorithm.

3. The proposed adaptive LFC strategy based on the FL and PSO technique

A large-scale interconnected power system, which is practically characterized by the nonlinearities, should be regulated efficiently by applying the robust and adaptive control strategies, including the LFC. In order to carry out an adaptive LFC scheme, a modern control method, e.g. fuzzy logic technique, can be considered as an efficient candidate due to its dominant advantages [4,5]. When implementing a FL mechanism, however, its scaling factors, which affect significantly the control characteristics of the system, need to be tuned properly by applying a robust technique. Meta-heuristic methods inspired from the biological science, such as the PSO algorithm, can be chosen to solve efficiently this problem.

3.1. Overview of the PSO algorithm

As a biological-inspired optimization technique, the PSO algorithm has been applied successfully in many control strategies. This method is based on the social behavior of a population, such as a flock of birds. Such a flock, which is assumed to be distributed randomly in a multidimensional search space of food, tends to move towards the destination of food. Each individual of this flock can certainly change its position with the random velocity to fly around the target. Obviously, the search will end when the above food source is met.

In practical applications of the PSO mechanism, each bird of such a flock can be considered as a particle of the corresponding swarm (or the individual of a population). Actually, each particle will represent a candidate for the solution of the search problem [7-10]. The PSO algorithm is implemented as described below.

(1) Step 1: Given randomly *n* particles of a swarm corresponding to an *n*-dimensional variable space. Also, there are a total of *m* swarms can be chosen to enhance the ability of the optimization method. At the beginning, each individual is initialized with a stochastic position and velocity (typically belong to a uniform distribution with the corresponding lower and upper bounds). Normally, two vectors of parameters using for the particles in the ith swarm at the beginning (t=0) are $\overline{P}_i^0 = \left(x_{i,1}^0, x_{i,2}^0, ... x_{i,n}^0 \right)$ and $\overline{V}_i^0 = \left(v_{i,1}^0, v_{i,2}^0, ... v_{i,n}^0 \right)$. Additionally, the lower and upper constraints of a swarm should be given by two vectors: $\overline{Lb}$ and $\overline{Ub}$. Also, to evaluate the convergence of each swarm when running the PSO mechanism, an objective function, f_{obj}, should be defined. This function will be calculated and compared to determine the local optimal parameters $\overline{P}_{i,best}$ at each time. The local optimal values obtained are then evaluated to identify the global optimal value $\overline{G}_{best}$. The determination of $\overline{P}_{i,best}$ and $\overline{G}_{best}$ should be conducted from the beginning (t = 0) to the final iteration (t = *N*).

(2) Step 2: Updating implementation in each iteration. At time t = k (or the kth iteration), both the velocity and position vectors of the ith swarm can be updated by using the following equations:

$$\overline{V}_i^{k+1} = \omega.\overline{V}_i^k + c_1.\xi_1 \left(\overline{P}_{i,best}^k - \overline{P}_i^k \right) \\ + c_2.\xi_2 \left(\overline{G}_{best}^k - \overline{P}_i^k \right) \quad (9)$$

$$\overline{P}_i^{k+1} = \overline{P}_i^k + \overline{V}_i^{k+1} \quad (10)$$

where, c_1 and c_2 are learning factors, ξ_1 and ξ_2 denote the positive numbers in [0, 1], and ω is the inertia weight coefficient. It is noted that when updating two above vectors, they should satisfy the constraint of the search problem. In addition, at an iteration of the optimization mechanism, both the local and global optimal values should also be updated.

(3) Step 3: Checking the stop criteria. Normally, the stop criteria can be the maximum value of iterations or the acceptable value of the objective function. The optimization mechanism will be terminated if one of such criteria is met.

3.2. Design an adaptive fuzzy logic LFC based on the PSO algorithm

The PSO algorithm mentioned above can be applied to design an adaptive LFC strategy using FL technique. The proposed control scheme is illustrated in Fig. 2. In order to understand clearly the working
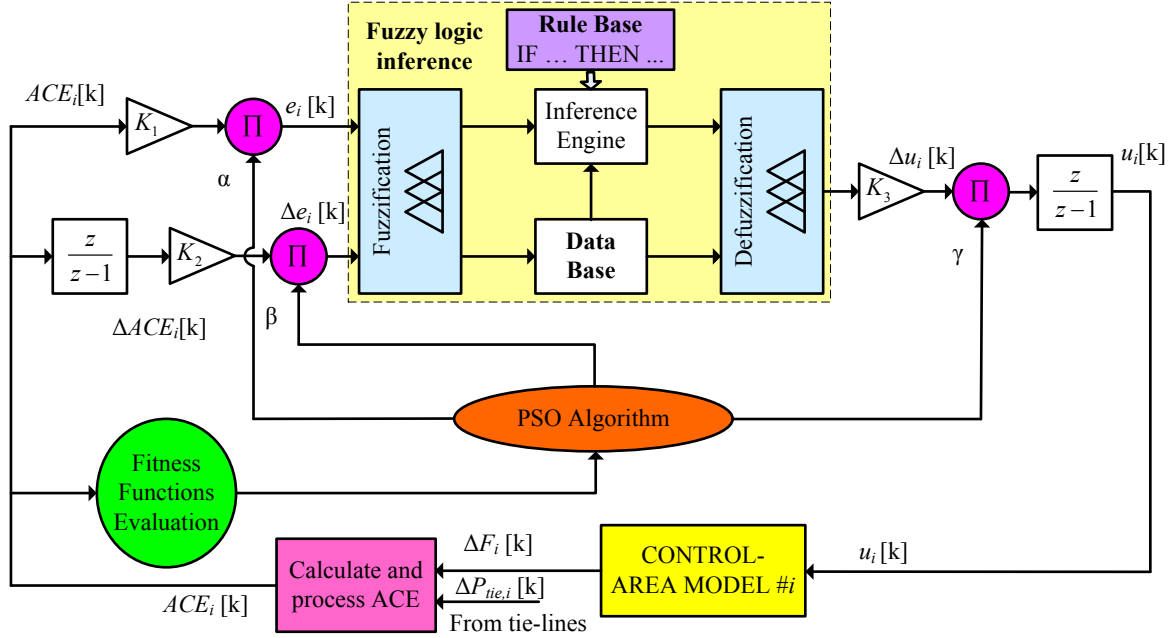
Fig. 2. The proposed adaptive PI-type fuzzy logic LFC based on PSO algorithm

mechanism of the PSO method for tuning the FL scaling factors, we first consider to analyze the principle of the proposed FL inference. As shown in Fig. 2, the FL inference without the PSO mechanism is based on a crisp relation as shown below:

$$\Delta u_i[k] = K_3 \left(\mu_1 K_1 . ACE_i[k] + \mu_2 K_2 . \Delta ACE_i[k] \right) \quad (11)$$

where, K_i ($i = 1, 2, 3$) and μ_j ($j = 1, 2$) denote the scaling factors and the inner gains of the FL inference, respectively.

The output control signal of the above FL controller can be calculated as:

$$u_i[k] = \Delta u_i[k] + u_i[k-1]. \quad (12)$$

From (11) and (12), by converting to the time domain, it is well known to yield the control signal as follows:

$$u_i(t) = K_P ACE_i(t) + K_I \int ACE_i(t) dt \quad (13)$$

where,

$$K_P = \mu_2 . K_2 . K_3 , \quad (14)$$

$$K_I = \mu_1 . K_1 . K_3 . \quad (15)$$

It is clear to see that two above factors, K_P and K_I, are similar to the proportional and integral coefficients of a PI regulator. The type of the proposed FL architecture is the PI-type FL as a result. When being treated as a PI-type FL controller, it is highly necessary to determine the optimal values of K_P and K_I since they affect strongly the output signal, and hence impact on the control quality of the system. From (14) and (15), to tune such two coefficients, the determination of three scaling factors K_i ($i = 1, 2, 3$) is the key problem to design an adaptive FL controller.

Table 2: The rule base of the PI-type FLC

$e_i[k]$	$\Delta e_i[k]$						
	BN	**MN**	**SN**	**ZE**	**SP**	**MP**	**BP**
BN	1	1	1	2	3	4	5
MN	1	1	2	3	4	5	6
SN	1	2	3	4	5	6	7
ZE	2	3	4	5	6	7	8
SP	3	4	5	6	7	8	9
MP	4	5	6	7	8	9	9
BP	5	6	7	8	9	9	9

In this study, the PSO algorithm will be employed to determine the scaling factors of the FL controllers applied to a large-scale multi-control-area power system to solve the problem of the LFC. In fact, if all of M-control-areas are applied the LFC, there will be $3M$ variables need to be optimized. As a result, the variable space of the PSO algorithm will be implemented with $3M$ parameters. This means that each group of K_i ($i = 1, 2, 3$) will be modified by using three updating factors α, β, and γ, respectively (see Fig. 2). In general, the new factors modifying from (14) and (15) are able to be obtained as follows:

$$K'_P = \mu_2 . (\beta . K_2) . (\gamma . K_3) , \quad (16)$$

$$K'_I = \mu_1 . (\alpha . K_1) . (\gamma K_3) . \quad (17)$$

The objective function is defined depending upon the aim of the LFC strategy, which would be to minimize the deviations of both the working system frequency and tie-line power flow.
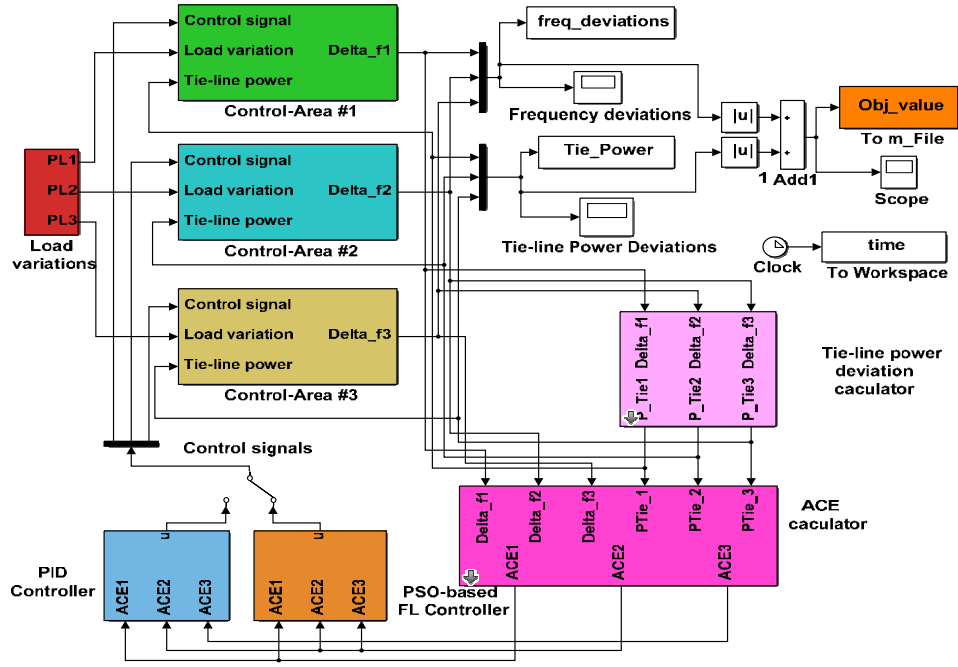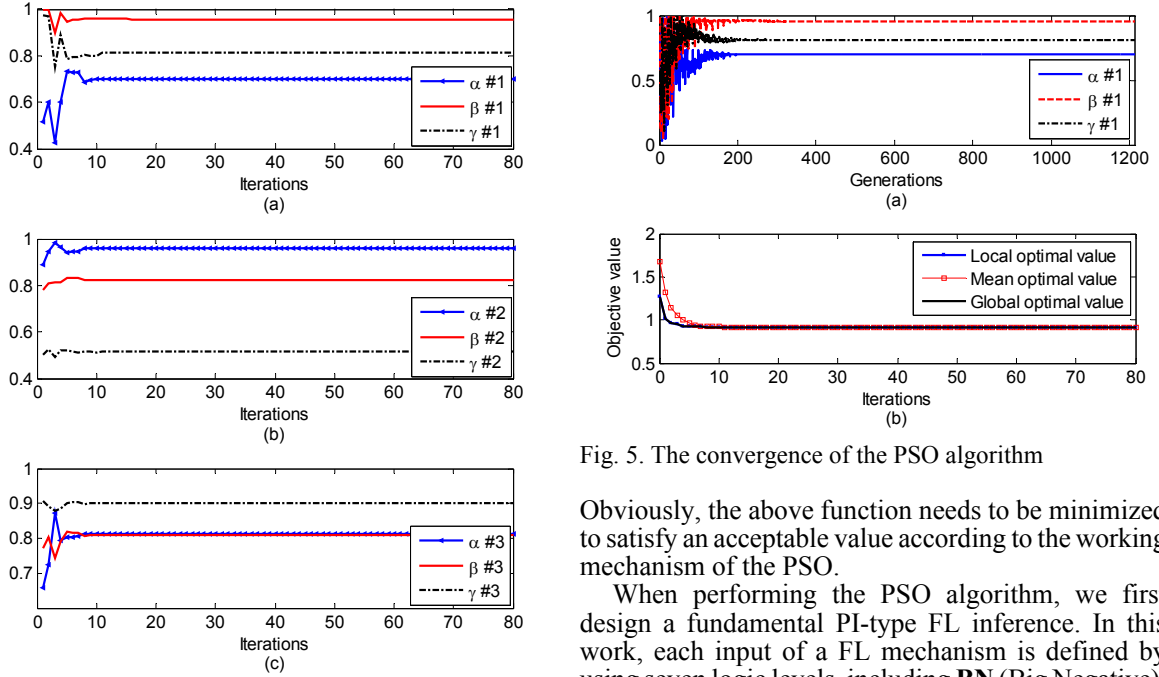
Fig. 3. Test system model built in Matlab/Simulink

Fig. 4. Updating values obtained to tune scaling factors

This objective function can be computed as:

$$f_{obj} = \int_{0}^{t} t.\sum_{i=1}^{M} \left(|\Delta f_i(t)| + |\Delta P_{tie,i}(t)| \right) dt. \qquad (18)$$

Fig. 5. The convergence of the PSO algorithm

Obviously, the above function needs to be minimized to satisfy an acceptable value according to the working mechanism of the PSO.

When performing the PSO algorithm, we first design a fundamental PI-type FL inference. In this work, each input of a FL mechanism is defined by using seven logic levels, including **BN** (Big Negative), **MN** (Medium Negative), **SN** (Small Negative), **ZE** (Zero), **SP** (Small Positive), **MP** (Medium Positive) and **BP** (Big Positive). Meanwhile, the output uses nine logic levels, namely, **BN** (Big Negative-**1**), **MN** (Medium Negative-**2**), **SN** (Small Negative-**3**), **VSN** (Very Small Negative-**4**), ZE (Zero-**5**), **VSP** (Very Small Positive-**6**), **SP** (Small Positive-**7**), **MP** (Medium Positive-**8**) and **BP** (Big Positive-**9**).

Table 3: Convergence results of the PSO algorithm

No. of generations	Area #1			Area #2			Area #3		
	α	B	γ	A	β	Γ	α	B	Γ
1	0.8055	0.9841	0.3846	0.0714	0.4177	0.2607	0.0835	0.6692	0.0688
2	0.5767	0.1672	0.5830	0.5216	0.9831	0.5944	0.1332	0.1904	0.3196
3	0.1829	0.1062	0.2518	0.0967	0.3015	0.0225	0.1734	0.3689	0.5309
4	0.2399	0.3724	0.2904	0.8181	0.7011	0.4253	0.3909	0.4607	0.6544
5	0.8865	0.1981	0.6171	0.8175	0.6663	0.3127	0.8314	0.9816	0.4076
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
1211	0.6998	0.9567	0.8131	0.9593	0.8233	0.5151	0.8128	0.8090	0.9006
1212	0.6998	0.9567	0.8131	0.9593	0.8233	0.5151	0.8128	0.8090	0.9006
1213	0.6998	0.9567	0.8131	0.9593	0.8233	0.5151	0.8128	0.8090	0.9006
1214	0.6998	0.9567	0.8131	0.9593	0.8233	0.5151	0.8128	0.8090	0.9006
1215	0.6998	0.9567	0.8131	0.9593	0.8233	0.5151	0.8128	0.8090	0.9006
Best value	**0.6998**	**0.9567**	**0.8131**	**0.9593**	**0.8233**	**0.5151**	**0.8128**	**0.8090**	**0.9006**

For this study, the corresponding rule base is indicated in Table 2. Also, the most popular case of symmetrically triangular membership functions is chosen for all of two inputs and one output of the proposed FL controller. These membership functions are of the standard range [-1, 1]. The following section will implement the numerical simulation process to verify the feasibility of the proposed control strategy.

4. Test system

Let us consider a three-control-area interconnected non-reheat power system as a typical case study to verify the feasibility of the proposed control strategy. The simulation model built in Matlab/Simulink environment is depicted in Fig. 3. The simulation parameters are given in Appendix of this paper. Here, both the PSO-PI-type FL controllers and PID regulators are used to deal with the LFC problem. Also, two simulation cases of load variations are implemented in this study. In the first case, load variations fed to the area #1, area #2 and area #3 are 0.01 p.u. (at 0s), 0.005 p.u. (at 2s) and 0.005 p.u. (at 4s), respectively. Simulation process is started by applying the PSO algorithm following three steps as mentioned earlier. Because of using three FL controllers, there are total of nine parameters in accordance with nine scaling factors need to be optimized. The convergence results of the PSO mechanism are represented in Fig. 4, Fig. 5 and Table 3. Obviously, with the parameters used (as indicated in Appendix), the PSO algorithm has been converged quickly after a few tens of iterations. As shown, not only the updating values (α_i, β_i, γ_i) but also the objective costs are totally converged towards the optimal values. As a result, the best optimal values can be obtained as illustrated in the last row of Table 3.

Using the optimal values obtained above, simulation results for the first case, plotted in Figs. 6-9, show that the PI-type FL controllers are able to
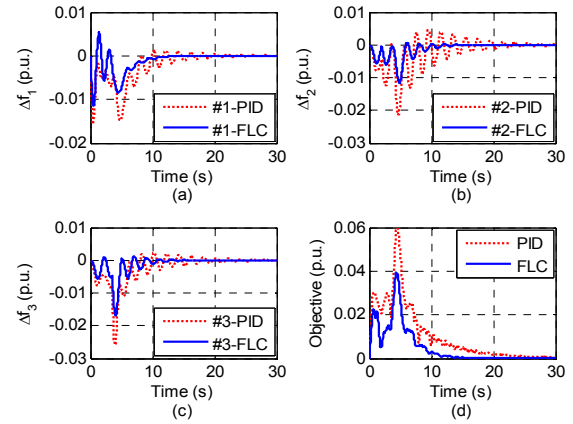

Fig. 6. Frequency deviations in the first simulation case

considerably outperform the PID regulators. Both the frequency and tie-line power flow deviations of the proposed controllers are damped more quickly compared with those of the PID counterparts. Fig. 8 and Fig. 9 illustrate a significant comparison regarding two main dynamic control characteristics: maximum undershoots and settling times. In fact, such two indices are usually used to evaluate the robustness and effectiveness of a control strategy.

In the second simulation case, the load variations, as shown in Fig. 10, are fed to the power system model. Here, the load changes continually and randomly in the first area, corresponding to the practical conditions. Similar to the first case, simulation results are plotted in Figs. 11-13. Fig. 13 represents a percent comparison in terms of undershoots and settling times between two given controllers. It can be explicitly said that the proposed control strategy is much more superior in comparison with the PID when dealing with the LFC issue. Thus, the PSO-PI-based FL controllers can be the feasible and optimal control solution for the LFC.
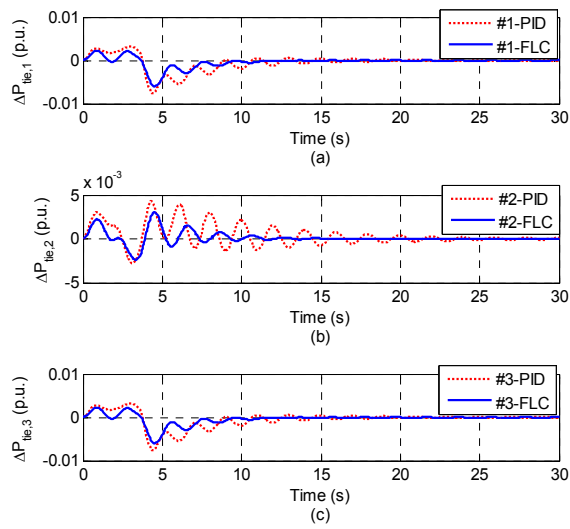
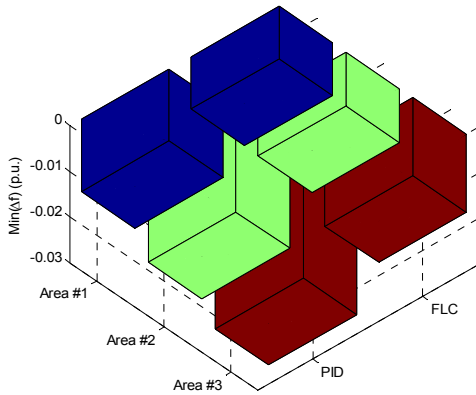Fig. 7. Tie-line power deviations in the first case

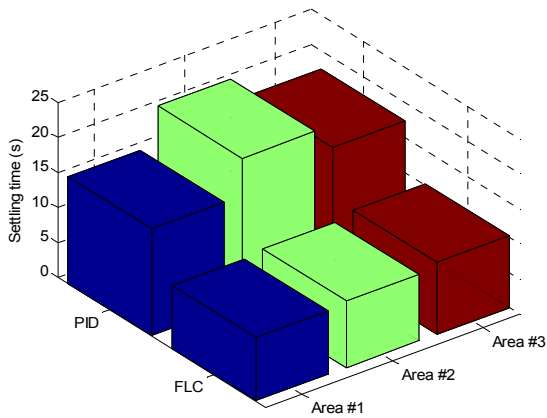Fig. 8. Maximum undershoots in the first case

Fig. 9. Settling times in the first simulation case with the given frequency tolerance: ε = 0.5%
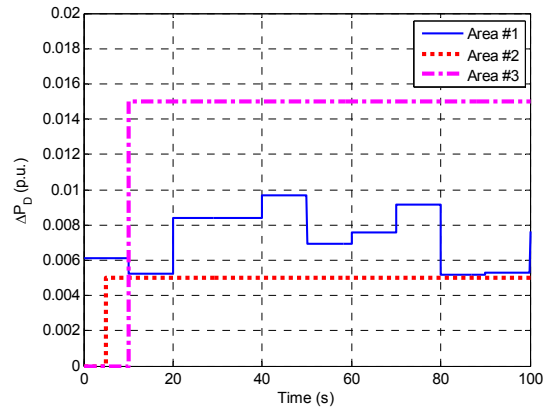

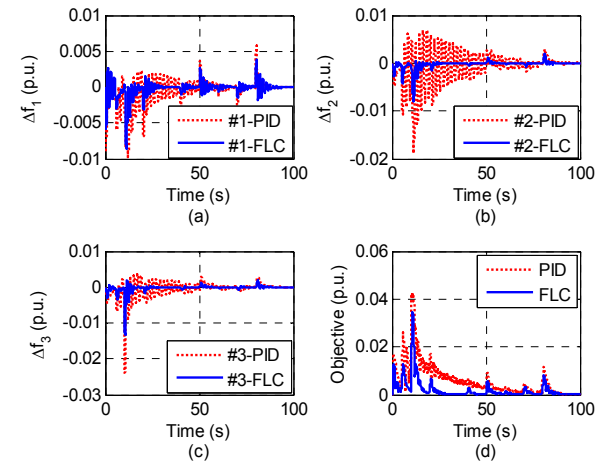Fig. 10. Load variations fed to power system in the second simulation case

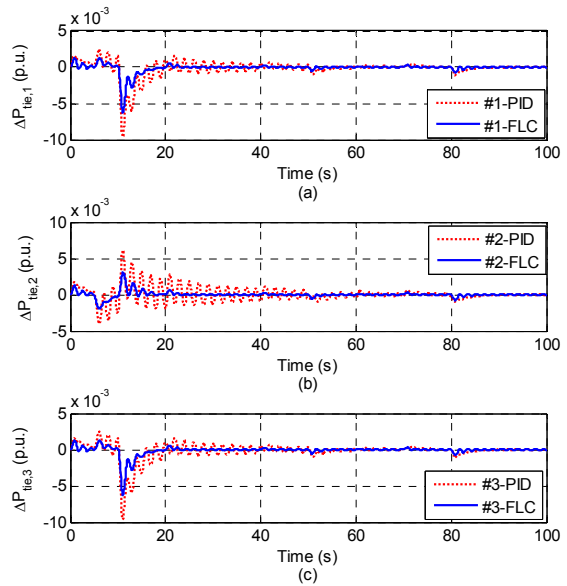Fig. 11. Frequency deviations obtained in the second simulation case

Fig. 12. Tie-line power flow deviations in the second simulation case
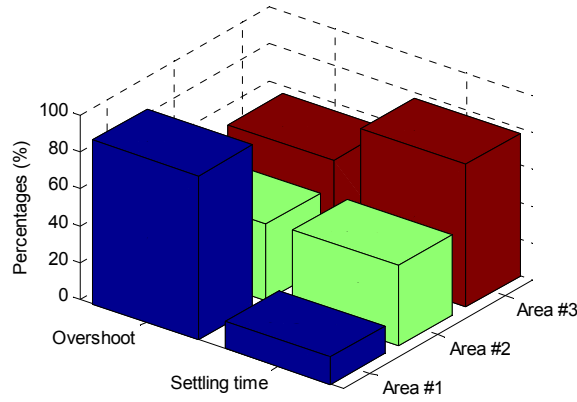
Fig. 13. A numerical comparison of the FLC and PID

5. Conclusion

The efficient application of the PSO algorithm to design an adaptive FL-based LFC strategy for a large-scale multi-control-area interconnected power system has been investigated in this paper. Each FL controller based on the PI type has three scaling factors (two for inputs and one for output) which need to be tuned to obtain the desirable control properties according to the objective of the LFC scheme. All of these scaling factors will be regulated to tune by using the PSO mechanism. A proper objective function has also been employed to make sure that the control quality can be achieved well enough to recover the stability of the system as rapidly as possible after load variations. The feasibility and effectiveness of the proposed control scheme have been demonstrated through a typical test system of three-control-area non-reheat power network with various load change conditions. Accordingly, the superiority of the PSO-FL-based controllers compared with the PID regulators has been confirmed assertively. For future work, the application of other meta-heuristic-inspired techniques, such as Genetic Algorithm, should be considered to compare with the PSO method mentioned in this study. In addition, these biological optimization mechanisms will be used to tune not only the scaling factors but also the membership functions as well as the rule base of the FL controllers applied for the LFC strategy. From this point, the practically large-scale electric power grids can apply efficiently these controllers to deal with urgent control problems in order to ensure their stability and economy.

Appendix

Parameters of a three-control-ara power system
$T_{G,1} = 0.08$, $T_{G,2} = 0.09$, $T_{G,3} = 0.12$
$T_{T,1} = 0.3$, $T_{T,2} = 0.28$, $T_{T,3} = 0.31$
$M_1 = 0.15$, $M_2 = M_3 = 0.18$
$D_1 = 0.0083$, $D_2 = D_3 = 0.0095$
$T_{ij} = 0.0707$

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