Turkish Journal of Electrical Engineering & Computer Sciences

http://journals.tubitak.gov.tr/elektrik/

Research Article

Turk J Elec Eng & Comp Sci
(2016) 24: 4900 – 4914

doi:10.3906/elk-1503-184

Applying metaheuristic optimization methods to design novel adaptive PI-type fuzzy logic controllers for load-frequency control in a large-scale power grid

ThiMaiPhuong DAO[1,2,*], **YaoNan WANG**[1], **NgocKhoat NGUYEN**[3,4]
[1]College of Electrical and Information Engineering, Hunan University, Changsha, Hunan, P.R. China
[2]Faculty of Electrical Engineering Technology, Hanoi University of Industry, Hanoi, Vietnam
[3]School of Energy Science and Engineering, University of Electronic Science and Technology of China, Chengdu, Sichuan, P.R. China
[4]Faculty of Automation Technology, Electric Power University, Hanoi, Vietnam

Received: 20.03.2015 • **Accepted/Published Online:** 03.10.2015 • **Final Version:** 06.12.2016

Abstract: Due to the complexity and diversity of large-scale power systems in practice, designing load-frequency control (LFC) strategies against load variations faces big challenges to ensure the stability and economy of the network. The focus of this paper is to design a novel adaptive PI-type fuzzy logic (FL)-based LFC architecture for solving the LFC problem in such an interconnected electric power grid. Applying 2 biologically inspired optimization methods, namely particle swarm optimization method and a genetic algorithm, the membership functions and rule base of a basic PI-type FL model were parameterized and optimized simultaneously and successfully. An online self-tuning method was adopted to adjust the output scaling factor, which significantly affects the control performances of the FL inference system. Thereafter, the proposed LFC strategy was applied to a typical 3-control-area power system with various load change conditions and generation units. Numerical simulations revealed the dynamic responses of the system frequency and tie-line power deviations verified the feasibility of the proposed controllers. It was found that such controllers, compared with the conventional PI regulators as well as other FL-based LFC models, can obtain better control performances. Major dynamic control indices, especially the overshoots and settling times, are effectively minimized to quickly recover the steady state of the network after random load changes, thus ensuring the stability and reliability of the system.

Key words: Load-frequency control, particle swarm optimization, genetic algorithm, online self-tuning method, PI-type fuzzy logic-based load-frequency control, large-scale electric power system

1. Introduction

Load-frequency control (LFC) in a large-scale interconnected power system mainly aims to maintain the grid frequency and tie-line power flow at their scheduled values against continual time-by-time load variations. It means that the dynamic oscillations of the working frequency and tie-line power deviations need to be damped as rapidly as possible [1–4]. In fact, a large-scale power network, composed of many generating stations or control areas, is highly complicated in practice [5,6]. Such an interconnected power grid can be particularly characterized by i) various types of generation units (including governors, turbines, and generators), ii) direct or indirect interconnection with other power systems, and iii) different load demands. The variety and complexity of the actual power systems bring challenges for operating the LFC in a stable network. As a result, it is necessary to design adaptive LFC controllers that are able to be applied more effectively to the electric power network in reality.

*Correspondence: daophuong@haui.edu.vn

To design an adaptive LFC strategy, modern intelligent techniques, e.g., fuzzy logic (FL), have been chosen as efficient control solutions [7–11]. The FL controllers, which should be seen as smart human-like decision tools, have been widely used in LFC schemes. In [7], a fundamental PI-type FL control architecture was proposed to tackle the LFC issue for a 4-area electric power interconnection. In [8], an indirect adaptive fuzzy control scheme to maintain the working frequency of a 3-area power system considering uncertainties was introduced. In [9,10], the authors presented a type-II FL-based LFC regulator, which was adopted for a 2-area thermal reheat electric power grid. In [11], an LFC method based on polar fuzzy controllers, which can act to restore the frequency and tie-line power to their nominal values in a smooth manner, was studied for a 3-area power system. Despite a large number of studies of LFC solutions based on the FL technique, they still need to be carefully considered when designing an adaptive control architecture that can tackle the LFC problem of a practical electric power interconnection as effectively as possible. In this context, it is highly necessary to modify the basic FL systems to further improve their superiority in dealing with the LFC scheme. Some of the fundamental issues concerning the PI-type FL controllers, especially the design of membership functions (MFs), fuzzy rule base, and tuning scaling factors, need to be carefully considered. It has been pointed out that all of these problems strongly affect the control performances of the system. Hence, when designing an adaptive FL-based LFC controller, its MFs and rule base should be parameterized and optimized to adapt to the variety of the practical power systems in order to achieve better control quality. This means that for such a complicated electric power grid, the optimal parameters in terms of the MFs and rule base must be generated to design an adaptive FL controller. Along with a suitable tuning method for the scaling factors, the LFC strategy for applying such adaptive FL controllers should be able to bring the stable-steady state back to the system as quickly as possible after load disturbances. Through the excellent control performances obtained, e.g., the lowest overshoots and the shortest settling times, the application of these FL controllers can guarantee the stability, reliability, and economy of the electric power grid.

In this study, following the aforementioned analyses, 3 tuning stages will be adopted to design an adaptive PI-type FL control strategy in solving the LFC problem. First, the particle swarm optimization (PSO) algorithm, a biological theory-based optimization method, will be utilized to optimize the parameters of the MFs. Second, another biological-inspired optimization technique, i.e. a genetic algorithm (GA), is used to design the optimal fuzzy rule base as well as the corresponding weighted factors. Finally, an online self-tuning method, which is operated based on a suitable FL inference system, is employed to tune the output scaling factor of the FL architecture [12]. A 5-step synchronous procedure of the above design method, applied to the FL-based LFC strategy, will also be presented in this work. With the effectiveness of the biology-based metaheuristic optimization techniques [13–15], i.e. PSO and GA, and the online self-tuning method, the adaptive PI-type FL controllers proposed in this study can become a promising control solution for LFC schemes. Numerical simulations will be performed for a case study, in which the proposed control methodology is applied to a 3-control-area interconnected thermal power network with various load variation conditions. The results obtained appear to validate the superiority and feasibility of the proposed control strategy.

The main contributions of this paper are presented below:

1) A reasonable integration of 2 well-known optimization methods, PSO and GA, is performed to utilize the advantages of each method and enhance the effectiveness of the whole control system.

2) An efficient coordination of the biological optimization methods and the online self-tuning method is implemented to optimize the MFs, rule base, weights, and output scaling factor of a PI-like FL inference

system.

3) A 5-step integrated procedure is proposed to design a 3-stage adaptive PI-type FL controller in dealing with the LFC problem of a complicated large-scale electric power grid. A 3-area power system model with different generation units and various load conditions, typically representative of large-scale power interconnections, was also successfully built to verify the effectiveness of the proposed control methodology over the other LFC methodologies.

The rest of this paper is organized as follows. Section 2 presents the mathematical model of a multiple control-area electric power interconnection for maintaining the network frequency based on tie-line bias control method. Section 3 then specifically describes 3 integrated stages and 5 synchronous steps, which are reasonably coordinated to design adaptive PI-type FL-based LFC architectures. The application of the 2 biological optimization methods, as well as the online self-tuning process, will also be represented in this section. In the next section, a multiple area large-scale power system with various types of turbines and generation units will be modeled and adopted as a typical simulation model to validate the feasibility of the proposed adaptive FL control strategy. An evaluation in comparison with different LFC schemes is also conducted in order to demonstrate the superiority of the novel control methodology studied in this paper. Finally, the conclusions and future works will be presented in Section 5.

2. Modeling for a multiple control-area interconnected-electric power grid

Each control-area in a large-scale interconnected-electric power grid, as shown in Figure 1, usually includes 3 basic components, namely the governor, turbine (prime mover), and generator-load unit. In this study, 2 common types of steam turbines, i.e. nonreheat and reheat turbines, are taken into account. The Laplace transfer functions of 2 such turbine types, as well as the governor and generator-load unit (considering the rotating mass of the machine), are presented in Table 1 [5,6]. The parameters used in this study corresponding to the above units can be found in the Appendix.

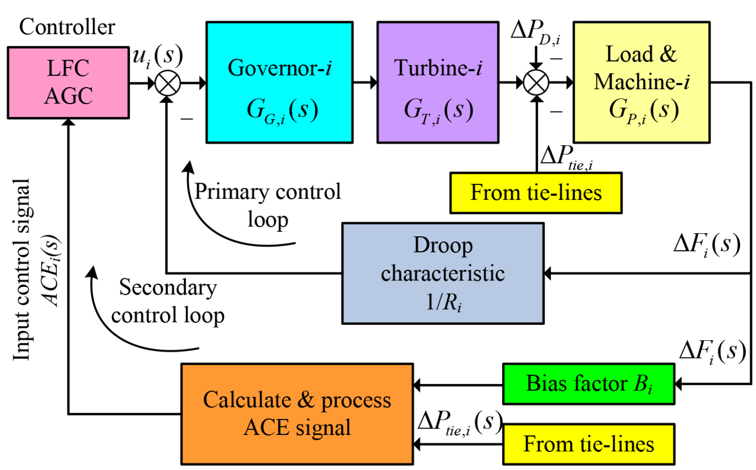

Figure 1. The LFC architecture of the ith control-area.

As shown in Figure 1, each generator in a power system is equipped with a proper governor, dealing with the primary control loop of the system frequency through a feedback coefficient of droop characteristic. The secondary control loop, which is based on the tie-line bias control scheme, is designed to realize the task of the LFC strategy. In principle, the feedback signal in this control loop, the ACE (area control error), is derived directly from the proportional combination of the frequency and tie-line power changes as expressed below [1–3,5]:

$$ACE_i(s) = \Delta P_{tie,i}(s) + B_i.\Delta F_i(s). \tag{1}$$

Such ACE signals are treated as the input of the load-frequency controller, which then generates the command signal for the primary control loop (see Figure 1).

Table 1. Transfer functions of 3 basic units of a control-area.

Turbine		Governor	Generator-load
Nonreheat	$G_{Tnr,i}(s) = \frac{1}{s.T_{Tnr,i}+1}$	$G_{G,i}(s) = \frac{1}{s.T_{G,i}+1}$	$G_{P,i}(s) = \dfrac{K_{P,i}}{s.T_{P,i}+1}$
Reheat	$G_{Tr,i}(s) = \frac{1}{s.T_{Tr,i}+1}.\frac{s.c_i T_{r,i}+1}{s.T_{r,i}+1}$		$= \dfrac{1}{s.M_i + D_i}$

3. Designing adaptive PI-type fuzzy logic-based load frequency controllers

A fundamental structure of a PI-type FL controller can be found in [7]. For designing a robust adaptive PI-type FL controller, 3 steps need to be implemented: 1) the definition of the MFs, 2) the design of a suitable rule base with the corresponding weights, and 3) the tuning of the output scaling factor. In order to perform these steps in seeking an adaptive control solution for the LFC issue, biological theory-based optimization techniques, such as PSO and GA, are employed in this study. The proposed control architecture is described in Figure 2. Here the PSO algorithm is adopted to define the MFs as the first phase. Then the GA technique is applied to determine the rule base and the corresponding weights as the second phase. The online self-tuning method is employed as the last step in order to generate the gain updating factor, which should be multiplied by the output scaling coefficient of the FL inference system [12]. The operation of each mechanism is discussed below.

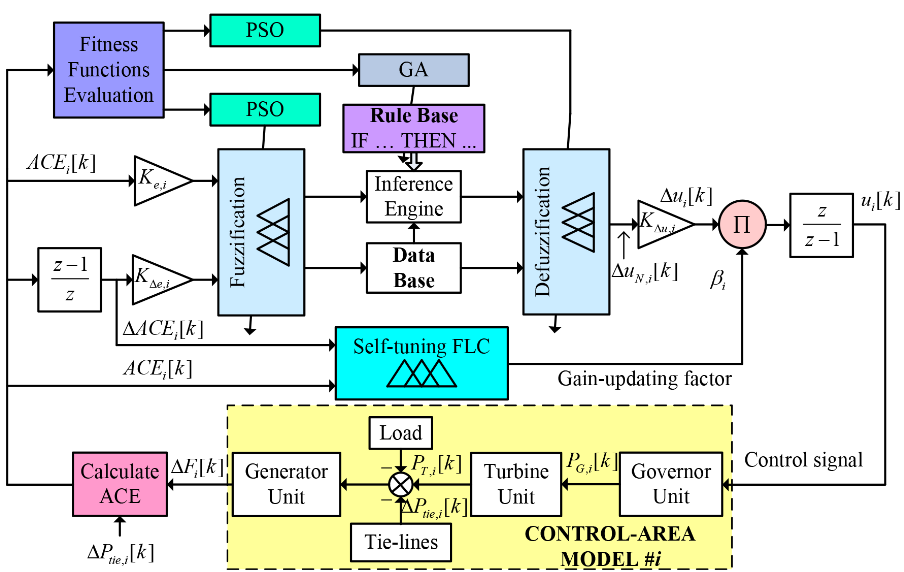

Figure 2. The proposed architecture of a 3-stage adaptive PI-type FL controller.

3.1. Applying the PSO algorithm to tune the membership functions

As a biologically inspired optimization technique, PSO has been applied successfully in a number of control strategies [13,14]. This mechanism is based on the social behavior of a population, e.g., a flock of birds. The metaphorical idea of the PSO method is explained briefly as follows. It is assumed that there are initially m particle swarms and each of them includes n individuals. At the kth iteration, the position and velocity of the ith swarm can be determined by 2 vectors, i.e. $\overrightarrow{P}_i^0 = (x_{i,1}^0, x_{i,2}^0, ...x_{i,n}^0)$ and $\overrightarrow{V}_i^0 = (v_{i,1}^0,\ v_{i,2}^0, ...\ v_{i,n}^0)$. All individuals of a swarm must be controlled to move towards the local optimal position, $\overrightarrow{P}_{i,best}$, which is evaluated by a fitness function. In addition, at each iteration, this best local position must be compared with the global optimal position, $\overrightarrow{G}_{best}$, which would be obtained from their previous neighbors. The new optimal vectors of global and local positions will then be determined and saved for the next step. The PSO algorithm is continued by updating the 2 vectors of position and velocity of the present swarm as:

$$\overrightarrow{V}_i^{k+1} = \omega.\overrightarrow{V}_i^k + c_1.\xi_1 \left(\overrightarrow{P}_{i,best}^k - \overrightarrow{P}_i^k\right) + c_2.\xi_2 \left(\overrightarrow{G}_{best}^k - \overrightarrow{P}_i^k\right), \tag{2}$$

$$\overrightarrow{P}_i^{k+1} = \overrightarrow{P}_i^k + \overrightarrow{V}_i^{k+1}, \tag{3}$$

wherec_1 and c_2 are learning factors, ξ_1 and ξ_2 denote random positive numbers in [0, 1], and ω is an inertia weight coefficient. When updating the above 2 vectors, they should satisfy the constraint of the search problem. For instance, the following constraint should be satisfied:

$$x_{L,j} \leq x_{i,j}^{k+1} \leq x_{U,j}, \tag{4}$$

where $x_{L,j}$, $x_{i,j}^{k+1}$, and $x_{U,j}$ denote the jth elements of the lower bound, position, and upper bound vectors, respectively. It is noted that the stop criteria, which are typically defined as the maximum values of iterations or the desired values of the fitness functions, should be checked at any iteration of the PSO mechanism. The optimization process will be terminated if 1 of the criteria is met.

In this study, the PSO algorithm is utilized to modify the fuzzy MFs. In order to simplify the design of an adaptive PI-like FL controller, 7 logic levels, including NB (negative big), NM (negative medium), NS (negative small), ZE (zero), PS (positive small), PM (positive medium), and PB (positive big), are used for all of its inputs and outputs. The standard symmetric-triangular fuzzy MFs are also employed for 2 such inputs and 1 such output. The basic rule base of the FL reasoning is described in Table 2.

To design the adaptive PI-type FL model, these MFs should be initially parameterized as depicted in Figure 3. It was found that there are 3 parameters used for each input or output of the FL inference model. For example, the first input ACE uses *aE*, *bE*, and *maxE* as its 3 variables. Eventually 9 parameters are adopted for 2 inputs (ACE, ΔACE) and 1 output (Δu) of the FL architecture. The standard bounds applied for each individual are $\overrightarrow{Lb}_{PSO}^0 = (-1,\ -1, -1,\ -1, -1,\ -1, -1)$ and $\overrightarrow{Ub}_{PSO}^0 = (1,\ 1, 1,\ 1, 1,\ 1, 1)$. These vectors are necessary to implement the PSO mechanism as mentioned earlier (see Eq. (4)). Additionally, to evaluate the convergence of the optimization problem, especially for the LFC strategy, a fitness function can be given as follows:

$$f_{PSO}^{fitness} = \int_0^t t.\sum_{i=1}^{M} (|\Delta f_i(t)| + |\Delta P_{tie,i}(t)|)dt. \tag{5}$$

Table 2. Basic rule matrix for designing the adaptive PI-type FL controller.

$ACE_i[k]$	$\Delta ACE_i[k]$						
	NB	NM	NS	ZE	PS	PM	PB
NB	NB	NB	NB	NM	NS	NS	ZE
NM	NB	NM	NM	NM	NS	ZE	PS
NS	NB	NM	NS	NS	ZE	PS	PM
ZE	NB	NM	NS	ZE	PS	PM	PB
PS	NM	NS	ZE	PS	PS	PM	PB
PM	NS	ZE	PS	PM	PM	PM	PB
PB	ZE	PS	PS	PM	PB	PB	PB

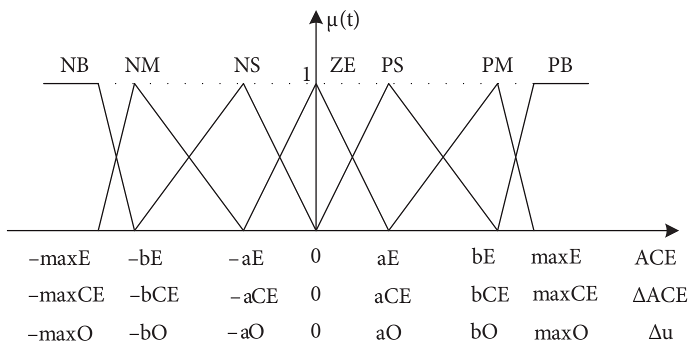

Figure 3. Parameterized process of MFs for a PI-type FL inference system.

Using the above PSO algorithm, the optimal parameters of fuzzy MFs can be obtained and they will be applied for the next optimization stage employing the GA method.

3.2. Genetic algorithm to optimize the rule base

The GA, which has been effectively applied in many adaptive and optimal control problems, is a super global-searching or metaheuristic algorithm [15]. Different types of problems are solved by means of the GA technique such as function optimization, routing problems, scheduling, neural network designing, adaptive control, and machine learning. As an effective biological optimization algorithm, the GA has been used much more widely than other counterparts in practice. Unlike the PSO technique, the working principle of the GA is based on the harsh natural selection of organisms. In principle, only the elite individuals with the most adaptive traits can survive in a fiercely competitive environment. The specific characteristics of natural selection, such as crossover, mutation, and recombination, are also applied to the GA in the optimization problem of control parameters. Such parameters will typically be encoded as binary strings before they are processed by the GA mechanism. Thus, a decoding process is also needed to convert the binary results into the optimal parameters for the control systems. The working mechanism of the GA was described specifically in [15].

In this study, to further optimize the control performances of the PI-type FL controller, the GA mechanism is employed to design an optimal rule base. Using the Mamdani model for the proposed FL architecture, each rule can be written as "*IF Input 1 (ACE) is* MF_p *and Input 2 (* ΔACE*) is* MF_q*, THEN Output (* Δu*) is* MF_r *(with the corresponding weight is* ω_r*)*". Here, p, q, and r are the indices of the MFs associated with the 7 linguistic values of NB, NM, NS, ZE, PS, PM, and PB for 2 inputs and 1 output of the proposed PI-type FL architecture. Therefore, the GA technique is utilized to optimize the parameters of each rule in terms of the linguistic value and the corresponding weight.

Because of having 49 fuzzy rules and 49 corresponding weights for the proposed FL inference system, there will be a total of 98 variables that need to be optimized. Furthermore, the lower and upper bounds of these variables can be determined depending on the encoding process and the characteristics of a Mamdani FL model as follows:

$$\overrightarrow{Lb}_{GA} = [ones(1,49),\ zeros(1,49)]\,, \tag{6}$$

$$\overrightarrow{Ub}_{GA} = [7.ones(1,49), ones(1,49)]\,, \tag{7}$$

where $zeros$(1,49) and $ones$(1,49) denote 1 $\times$ 49 matrixes of zeros and ones, respectively. The flow chart of the GA-based fuzzy rule optimization applied to this work is presented in Figure 4. In the first step of the method, all necessary parameters are initialized, including the population size (n_{pop}), number of variables (n_{var} = 98), number of maximum iterations (n_{iter}), and the termination criterion (the acceptable tolerance of the fitness function ε). In the second step, the fitness function employed for the GA mechanism is defined as below:

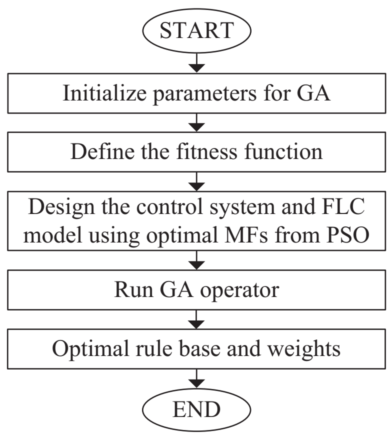

Figure 4. Flow chart for the GA procedure to optimize rule base and weights.

$$f_{GA}^{fitness} = \int_0^t t.\sum_{i=1}^{M} |ACE_i(t)|dt, \tag{8}$$

where M is the number of control areas in the interconnected power system. In the third step, an electric power grid model with FL-based LFC controllers is built to evaluate the fitness function value computed for an iteration of the GA mechanism. Such FL architecture utilizes the MFs derived directly from the optimal results of the PSO algorithm, as mentioned earlier. After running the GA operation, the optimal rule base together with the corresponding weights can be obtained. They are then applied for the following phase to design an adaptive PI-type FL inference system.

3.3. Online self-tuning method to adjust the output scaling factor

It is well known that the output scaling factor of an FL inference model significantly affects the performance and qualification of a control system. Therefore, it needs to be tuned in order to design a robust FL architecture in the optimal control strategy. In this study, the online self-tuning method is used due to its simple and efficient implementation [12]. According to this method, other FL reasoning is added to the system. Such an FL model also uses 2 inputs (ACE and ΔACE) to create the gain-updating factor β, which is multiplied by the output scaling factor $K_{\Delta u}$ (see Figure 2). Hence, the output signal of the PI-type FL control architecture can be computed as:

$$\Delta u_i[k] = \beta_i.K_{\Delta u,i}.\Delta u_{N,i}[k], \tag{9}$$

where $\Delta u_{N,i}[k]$ is the internal output of the FL inference model (see Figure 2). As a result, the new output scaling factor can be obtained as follows:

$$K'_{\Delta u} = \beta_i.K_{\Delta u,i}. \tag{10}$$

It is clear that the change of the gain-updating factor β_i, which can be attained according to the trend of 2 inputs (ACE and ΔACE), will affect the value of the output signal given in Eq. (9). This means that such an output can be updated to achieve the optimal value in the search for the control strategy. The output variable β_i is represented by the symmetric-triangular MFs with a suitable-limited interval [0, 1] as illustrated in Figure 5. Here, 7 linguistic variables are used for the output signals of gain-updating factor β_i, including ZE (zero), VS (very small), S (small), SB (small big), MB (medium big), B (big), and VB (very big). In order to further optimize the main control performances, such as the overshoot and settling time, when dealing with the LFC strategy, the rule base designed for the β-*FLC* should be based on the following principles:

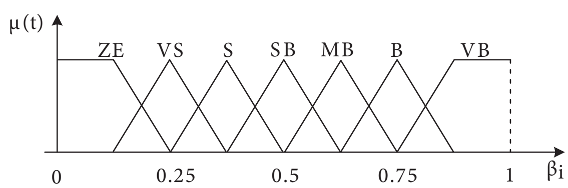

Figure 5. Membership functions of the output gain-updating factor.

1) If ACE is big (NB or PB) and the sign of ΔACE is opposite to ACE, then β will be set as a small value.

2) If ACE is small and moving far away from zero, while ΔACE is sufficiently large, then β should be a large value.

3) If either ACE or ΔACE is zero, then β is near the medium value.

4) If both of the 2 inputs are zero, then β should be zero.

3.4. Synchronous procedure to design the adaptive FL controller

In order to design an adaptive 3-stage PI-type FL inference architecture for the LFC strategy, as discussed earlier, it is necessary to integrate the executed procedures. Accordingly, a synchronous 5-step process is proposed in this work as follows:

Step 1: Design a control system. In particular, a multiple control-area interconnected power system needs to be determined as a control plant. For this study, a 3-control-area electric thermal power system with various load conditions and generation units was modeled as the control plant to tackle the LFC problem.

Step 2: Design the PI-type FL architecture. As discussed earlier, the load-frequency regulator built for each control-area of the network was based on the PI-type FL model. Such a controller, using the Mamdani model, needs to be parameterized in terms of fuzzy rules as well as the MFs to apply the optimization techniques (see Section 3.1).

Step 3: Apply the PSO algorithm. The optimization process begins with the PSO mechanism to optimize the parameters of the MFs for designing the PI-type FL controller. To implement this process, a standard rule base (as illustrated in Table 2) was initially applied. The executed steps are indicated specifically in Section 3.1.

Step 4: Apply the GA technique. The following step used for the optimization is to apply the GA technique as discussed in Section 3.2. Here, both the rule base and a set of the corresponding weights are optimized to design the adaptive FL inference model. It was noted that the MFs employed for the FL reasoning are derived directly from the optimal results of the PSO algorithm in the third step.

Step 5: Realize the online self-tuning method. The last step for designing a robust FL controller is to use the self-tuning scaling factor method. The FL model should adopt the optimized parameters of the MFs and rule base obtained from the previous steps. This process was carried out to further enhance the control quality of the LFC scheme.

With the above 5 steps, the design process of a robust 3-stage PI-type FL controller was completed in order to ensure the optimal quality of the control system. The following section provides numerical simulations for the validation purpose of the control superiority of the adaptive PI-type FL controllers presented in this paper.

4. Test system

In order to validate the feasibility and superiority of the proposed FL control strategy, in this section, a practical complicated 3-area thermal power system is taken into account. It is assumed that the first area contains 3 generation units, using nonreheat turbines with 3 participant powers: 300 MW, 300 MW, and 400 MW. This control-area is interconnected directly with the other 2 areas to exchange the scheduled power. The 2 remaining control areas are simplified as single generation units using reheat turbines. On the other hand, these areas are assumed to be indirectly interconnected and their loads may occur independently. The simulation parameters of 3 control-areas can be found in the Appendix.

Before starting the simulation process, however, the governor-turbine-generator units of the first area should be lumped to simplify the implementation. Using the simplifying method as mentioned in [5,6], 3 generation units in such a control-area can be replaced with only 1 simple area, including the governor, nonreheat turbine, and generator-load unit. The simplifying theorem is represented as follows:

Simplifying theorem: Assuming that there are m generators connected in parallel, they can be replaced with an equivalent generator unit, which is represented as

$$G_{Peq,i}(s) = \frac{1}{\sum\limits_{k=1}^{m} \eta_k.D_k + s.\sum\limits_{k=1}^{m} \eta_k.M_k} = \frac{1}{D_{eq,i} + s.M_{eq,i}}, \tag{11}$$

where D_k, M_k, and η_k denote the load damping factor, the inertia constant of the kth generator in area $\#i$, and the participating factor representing its generation contribution, respectively.

The above theorem is able to be effectively applied for the other units, such as the governor and turbine, in the same manner. After some necessary calculations based on this theorem, the corresponding transfer functions of the 3 lumped components can be respectively given as follows:

$$G_{G,1}(s) = \frac{1}{0.066s + 1}, \tag{12}$$

$$G_{T,1}(s) = \frac{1}{0.348s + 1}, \tag{13}$$

$$G_{P,1}(s) = \frac{1}{0.182s + 0.009}. \tag{14}$$

The substituted speed regulation R_1 is computed to be equal to 2.59 from the parameters assumed in the Appendix.

Applying the 5 steps of the optimization process as presented previously, a robust adaptive FL controller with optimal parameters can be obtained. To adapt to the complexity of the present power system, all the parameters, including the MFs, rule base, and weights, need to be optimized based on the PSO and GA techniques. Figure 6a shows the 3D graph of the fundamental PI-type FL architecture in accordance with Table 2. Meanwhile, Figure 6b plots the final FL reasoning, which has been obtained according to the PSO-based optimization method. The comparisons between the proposed adaptive FL-based control methodology and the conventional PI regulators as well as the other FL-based controllers in dealing with the LFC issue is specifically presented below.

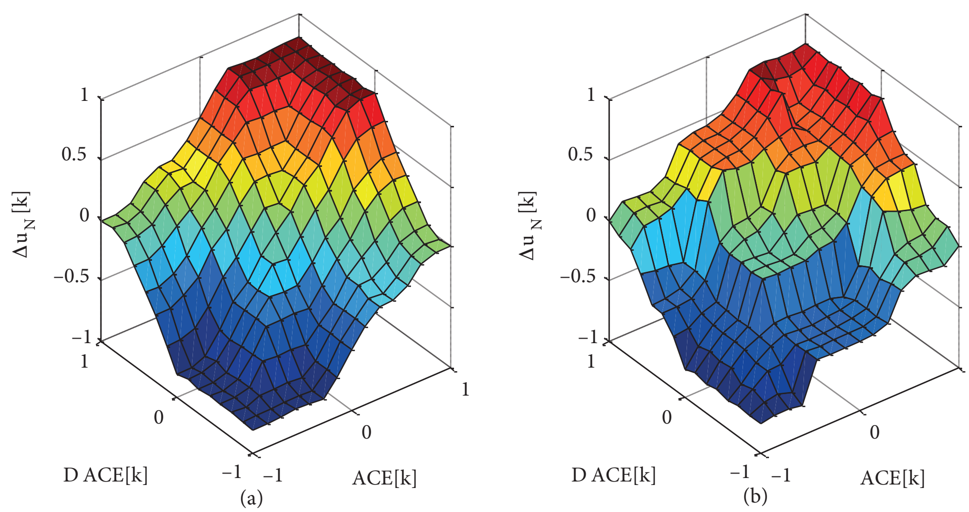

Figure 6. An illustration of the fuzzy inference systems in 3D graphs: a) The fundamental FL architecture, b) the optimal FL architecture.

4.1. Effectiveness of the proposed control scheme over the PI regulators

Figures 7 and 8 and Table 3 illustrate the effectiveness of the proposed adaptive FL controllers in comparison with the conventional PI regulators. Figures 7a–7c plot the dynamic frequency deviations for the first, second, and third area, respectively. Meanwhile, Figure 7d shows the sum of absolute values of the frequency changes in all 3 areas. Similarly, Figures 8a–8d describe the tie-line power changes in 3 control areas and the total of the absolute values of all ACE signals for these 3 areas, respectively. These figures clearly show that the transient oscillations of both the system frequency and tie-line power deviations as well as ACE signals of the proposed FL architectures are extinguished much more quickly than those of the conventional PI regulators. In order to assess numerically the simulation results, given a desirable frequency tolerance ($?_f = 0.5\%$), the absolute overshoots and settling times of 3 control areas, which are in percentages for comparison purposes, can be calculated and are indicated in Table 3. It was clearly seen that the proposed FL controllers achieved outstanding effectiveness compared with the traditional PI regulators. All the comparison results by means of the novel FL regulator in percentage terms are, in total, less than 100% (see Table 3). Thus, the proposed adaptive FL control methodology was able to robustly outperform the conventional PI regulator when realizing the LFC strategy.

Table 3. A comparison in percentages for all control-areas concerning 2 control indices.

Control-area	Overshoot (%)	Settling time (%)
Area #1	40.4657	39.1863
Area #2	41.0447	54.6423
Area #3	45.4223	47.5981

4.2. Effectiveness of the proposed control scheme compared with the other FL-based controllers

In order to verify the robustness of the proposed adaptive FL-based control strategy over the other representatives of the PI-like FL regulators, several simulation results for comparison purposes were implemented, as shown in Figures 9 and 10. Here, besides the proposed adaptive FL regulator, 4 other FL-based controllers were taken into account, including the basic PI-FL model introduced in [7], the FL type-II presented in [10], and the PSO-based FL and GA-based FL architectures. The last 2 control methodologies were built depending only upon either the PSO or the GA method to tune the MFs and rule base, as well as the scaling factors of the FL inference system. As shown in the figures, especially in Figure 10, the proposed adaptive control scheme was able to completely outperform not only the conventional PI regulator but also the other FL architectures

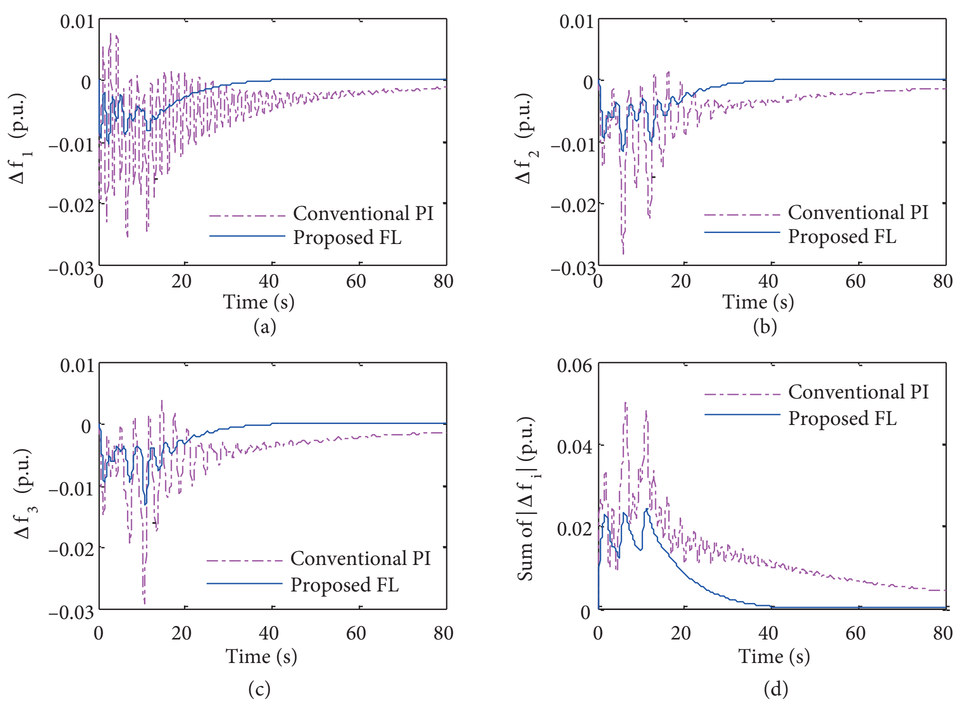

Figure 7. A comparison of frequency deviations between the proposed FL and PI: a) Area #1, b) Area #2, c) Area #3, d) sum of absolute values.

in dealing with the LFC problem. The main control indexes obtained, such as smaller overshoots (shown in Figure 10a) and shorter settling times (shown in Figure 10b), are more promising for practical application in a modern electric power grid. Therefore, it can be said that the FL-based control methodology proposed in this work is capable of replacing a large number of other conventional and FL-based LFC strategies. The excellent viability of this novel control method has also been proven.

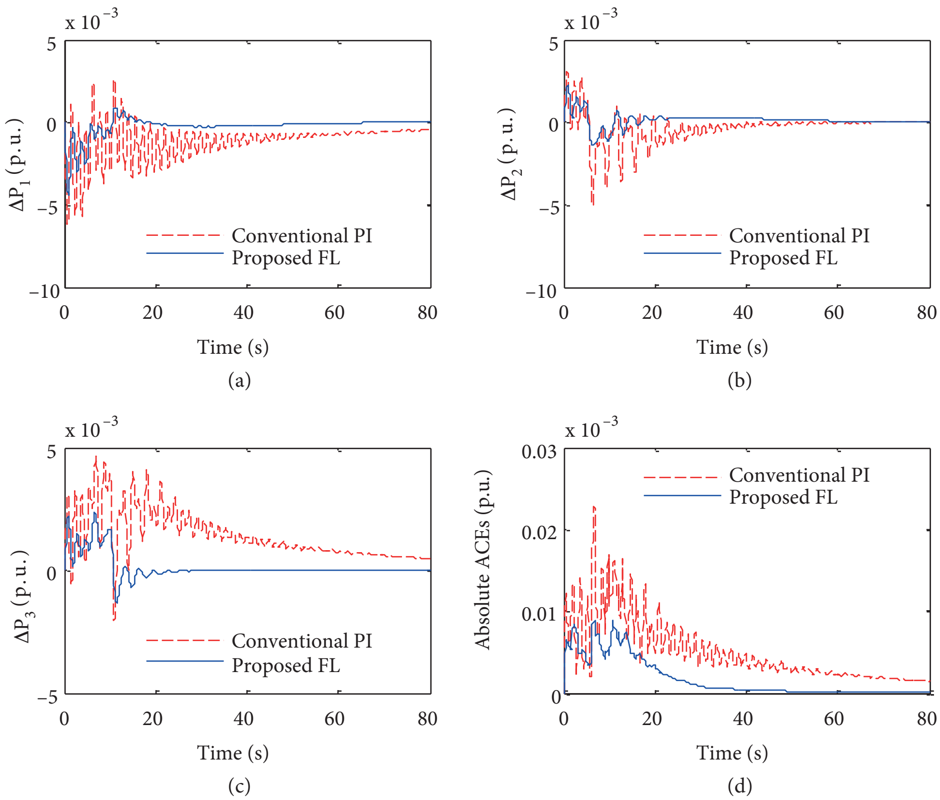

Figure 8. A comparison of tie-line power changes and absolute value of ACE signals for PI and proposed FL controllers: a) Area #1, b) Area #2, c) Area #3, d) sum of absolute values.

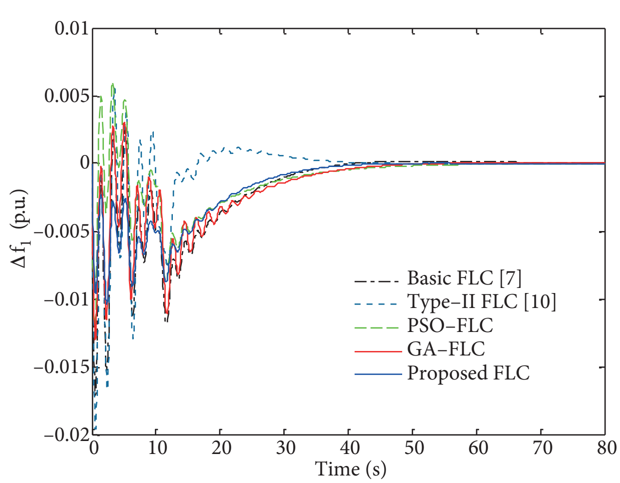

Figure 9. A comprehensive comparison regarding the frequency deviations in the first area for different controllers.

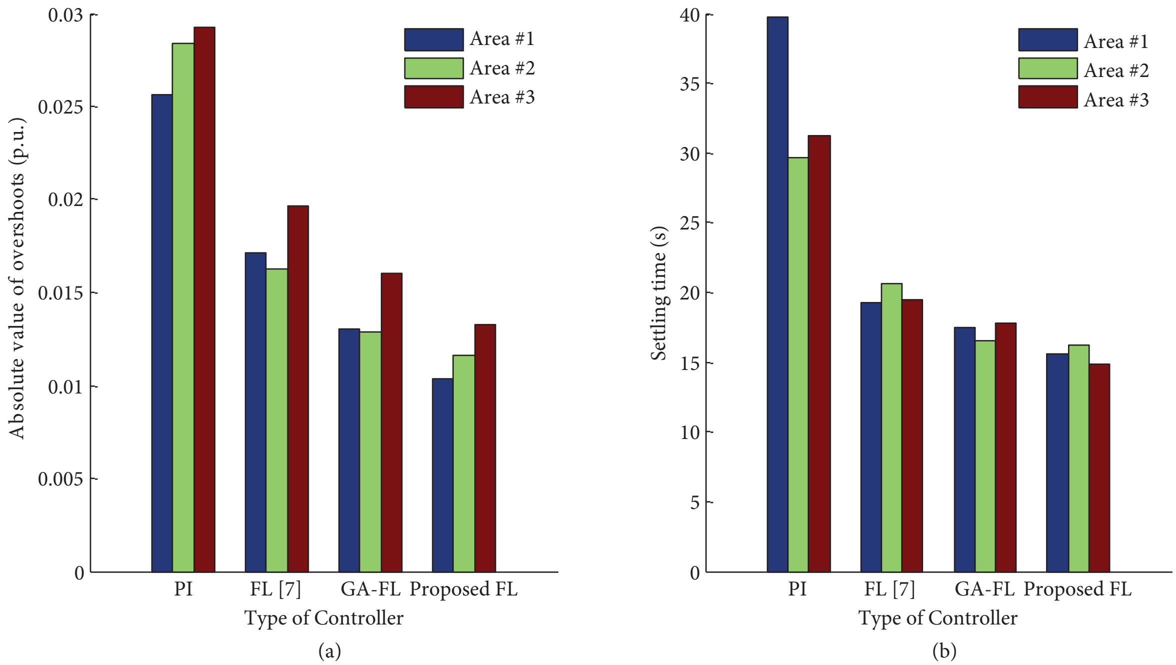

Figure 10. Numerical comparison in 3-control-area thermal power system using different load-frequency control controllers: a) overshoots, b) settling times.

5. Conclusions, discussion, and future work

The main contribution of this paper is to propose a novel idea to design an adaptive PI-type FL-based LFC methodology for a multiple area interconnected electric power grid. To build this control strategy, 3 main stages need to be implemented synchronously, including: 1) the MFs are optimized by applying the PSO algorithm; 2) the rule base and weights are optimized by using the GA technique; and 3) the output scaling factor is tuned by means of a suitable FL reasoning model. To fulfill these 3 designing stages, a 5-integrated-steps procedure has been represented in this work. Applying this integrated procedure, the FL inference system with optimal parameters was successfully built, utilizing the advantages of both the well-known optimization methods (i.e. PSO and GA) and the FL-based tuning model.

The proposed LFC strategy, as well as the conventional PI regulator and the other 4 FL-based control architectures, were applied to a 3-control-area interconnected power system using various generation units, different load conditions, and complicated structures. This model is representative of practical large-scale power systems in dealing with the LFC problem. Simulation results obtained by means of the novel FL control architecture with outstanding performances, such as the desired frequency and tie-line power deviations, demonstrated the superiority of this proposed LFC scheme over the other ones. The proposed control methodology is therefore capable of successfully replacing the traditional PI regulators and the fundamental FL-based models in finding an efficient solution for the LFC issue. As a result, the effectiveness and the feasibility of the proposed control strategy are both highly promising for applications in practical complex power grids.

Ongoing studies should focus on modeling highly complex electric power grids in reality to validate the superiority of the proposed control scheme to tackle the LFC problem. Furthermore, some characteristics of such a practical large-scale power system, e.g., uncertainties, nonlinearities, and communication time delays, might be of considerable concern for our future work. For example, communication time delays, which may be inevitable due to communication links, especially in a large-scale power system with very long distance transmission lines, can degrade dynamic control performances, thus affecting the stability and reliability of the closed LFC loops. As a result, dealing with this phenomenon in an efficient coordinated manner with the proposed LFC strategy should be some of the most interesting future studies arising from the present work.

Nomenclature

i	index of the control-area $\#i$, $i = 1, 2, \ldots n$
f	real frequency of the network, Hz
$\Delta F_i\ (s)$	frequency deviation, in Laplace domain, p.u.
$\Delta P_{D,i}$	load variation, p.u.
$\Delta P_{tie,i}$	tie-line power flow deviation, p.u.
$T_{G,i}$	time constant of governor, s
$T_{T,i}$	time constant of turbine unit, s
D_i	load damping factor, p.u. MW/Hz
M_i	load-generator inertia constant, p.u.
$K_{P,i}$	gain of load-generator unit, Hz/p.u. MW
$T_{P,i}$	time constant of load-generator unit, s
T_{ij}	tie-line time constant of the area $\#i$ and area $\#j$, s
B_i	frequency bias factor, MW/p.u. Hz
R_i	speed regulation, Hz/MW

Acknowledgment

This work was supported by the National Natural Science Foundation of China (Grants No: 6117075, 60835004, and 61104088) and the National High Technology Research and Development Program of China (863 Program) (2012AA111004, 2012AA112312).

References

[1] Aidin S, Gevork BG, Seyed HH. Decentralized robust load-frequency control of power system based on quantitative feedback theory. Turk J Elec Eng & Comp Sci 2011; 19: 513-530.

[2] Tarkeshwar, Mukherjee V. A novel quasi-oppositional harmony search algorithm and fuzzy logic controller for frequency stabilization of an isolated hybrid power system. Electr Pow Energ Syst 2015; 66: 247-261.

[3] Doha GP, Somanath M. A new control scheme for PID load frequency controller of single-area and multi-area power systems. ISA T 2013; 52: 242-251.

[4] Ali ES, Abd-Elazim SM. BFOA based design of PID controller for two area load frequency control with nonlinearities. Electr Pow Energ Syst 2013; 51: 224-231.

[5] Wood AJ, Wollengerg BF, Sheble GB. Power Generation, Operation, and Control. New York, NY, USA: Wiley, 2013.

[6] Tan W, Zhou H. Robust analysis of decentralized load frequency control for multi-area power systems. Int J Elec Power 2012; 43: 996-1005.

[7] Nguyen NK, Huang Q, Dao TMP. On design of robust PI-based fuzzy logic controllers for load-frequency control in a large-interconnected power system. J Electr Eng 2014; 14: 325-330.

[8] Hassan AY, Khalfan MAK. Indirect adaptive fuzzy logic frequency control of multi-area power system. In: IEEE 2015 Proceedings of the 8th GCC Conference and Exhibition; 1–4 February 2015; Muscat, Oman. New York, NY, USA: IEEE. pp. 1-6.

[9] Yousef HA, Kharusi KA, Albadi MH, Hosseinzadeh N. Load frequency control of a multi-area power system: an adaptive fuzzy logic approach. IEEE T Power Syst 2014; 29: 1822-1830.

[10] Venkatraman E, Velusami S, Mohamed TAM, Ganapathy S. Design of type-II fuzzy logic load frequency controller for two area thermal reheat power systems. In: IEEE 2012 Computing, Electronics and Electrical Technologies International Conference; 21–22 March 2012; Kumaracoil, India. New York, NY, USA: IEEE. pp. 180-185.

[11] Chaturvedi DK, Umrao R, Malik OP. Adaptive polar fuzzy logic based load frequency controller. Electr Pow Energ Syst 2015; 66: 224-231.

[12] Mudi RK, Pal NR. A robust self-tuning scheme for PI- and PD-type fuzzy controllers. IEEE T Fuzzy Syst 1999; 7: 2-16.

[13] Kaushik DS, Amitava C, Anjan R. A hybrid approach for design of stable adaptive fuzzy controllers employing Lyapunov theory and particle swarm optimization. IEEE T Fuzzy Syst 2009; 17: 329-342.

[14] Bevrani H, Daneshmand PR. Fuzzy logic-based load-frequency control concerning high penetration of wind turbines. IEEE Syst Journal 2012; 6: 173-180.

[15] Daneshfar F, Bevrani H. Load-frequency control: a GA-based multi-agent reinforcement learning. IET Gener Transm Dis 2010; 4: 13-26.

Appendix

Parameters of 3-control-area thermal power system model:

$M_{11} = 0.18,\ D_{11} = 0.01,\ T_{Gnr,11} = 0.060,\ T_{Tnr,11} = 0.41,\ P_{11} = 300$MW, $\mathrm{R}_{11} = 2.5$

$M_{12} = 0.16,\ D_{12} = 0.008,\ T_{Gnr,12} = 0.055,\ T_{Tnr,12} = 0.35,\ P_{12} = 300$MW, $\mathrm{R}_{12} = 2.4$

$M_{13} = 0.20,\ D_{13} = 0.009,\ T_{Gnr,13} = 0.080,\ T_{Tnr,13} = 0.30$, $\mathrm{P}_{13} = 400$MW, $\mathrm{R}_{13} = 2.8$

$B_{11} = B_{12} = B_{13} = 0.425$

$T_{Gr,2} = T_{Gr,3} = 0.2,\ T_{Tr,2} = T_{Tr,3} = 20,\ c_2 = c_3 = 0.333,\ T_{T,2} = T_{T,3} = 0.3,\ K_{P,2} = K_{P,3} = 120,$

$T_{P,2} = T_{P,3} = 18,\ R_2 = R_3 = 2.4$

PSO parameters: $n = 9,\ m = 15,\ N = 30,\ n_{generations} = 465$

GA parameters: $n_{pop} = 20,\ n_{gen} = 30,\ n_{elite} = 2$