Robust modified GA based multi-stage fuzzy LFC

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Abstract

In this paper, a robust genetic algorithm (GA) based multi-stage fuzzy (MSF) controller is proposed for solution of the load frequency control (LFC) problem in a restructured power system that operates under deregulation based on the bilateral policy scheme. In this strategy, the control signal is tuned online from the knowledge base and the fuzzy inference, which request fewer sources and has two rule base sets. In the proposed method, for achieving the desired level of robust performance, exact tuning of the membership functions is very important. Thus, to reduce the design effort and find a better fuzzy system control, membership functions are designed automatically by modified genetic algorithms. The classical genetic algorithms are powerful search techniques to find the global optimal area. However, the global optimum value is not guaranteed using this method, and the speed of the algorithm’s convergence is extremely reduced too. To overcome this drawback, a modified genetic algorithm is being used to tune the membership functions of the proposed MSF controller. The effectiveness of the proposed method is demonstrated on a three area restructured power system with possible contracted scenarios under large load demand and area disturbances in comparison with the multi-stage fuzzy and classical fuzzy PID controllers through FD and ITAE performance indices. The results evaluation shows that the proposed control strategy achieves good robust performance for a wide range of system parameters and load changes in the presence of system nonlinearities and is superior to the other controllers. Moreover, this newly developed control strategy has a simple structure, does not require an accurate model of the plant and is fairly easy to implement, which can be useful for the real world complex power systems.

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Keywords: LFC; Multi-stage fuzzy controller; Restructured power system; Fuzzy switch; GAs; Power system control

1. Introduction

The dynamic behavior of many industrial plants is heavily influenced by disturbances and, in particular, by changes in the operating point. This is typically the case for restructured power systems. Load frequency control (LFC) is a very important issue in power system operation and control for supplying sufficient and reliable electric power with good quality. The main goal of LFC is to maintain zero steady state errors for frequency deviation and good tracking of load demands in a multi-area power system. In addition, the power system should fulfill the requested dispatch conditions. A lot of studies have been made in the last two decades about LFC in interconnected power systems [1–11].

The real world power system contains different kinds of uncertainties due to load variations, system modeling errors and change of the power system structure. As a result, a fixed controller based on the classical theories is certainly not suitable for solution of the LFC problem. Consequently, it is required that a flexible controller be developed. The conventional control strategy for the LFC problem is to take the integral of the area control error as the control signal. An integral controller provides zero steady state deviation, but it exhibits poor dynamic performance [2]. To improve the transient response, various control strategies, such as linear feedback, optimal
control and variable structure control have been proposed [3–5]. However, these methods need some information for the system states, which are very difficult to know completely. There have been continuing efforts in designing LFC with better performance to cope with the plant parameter changes using various adaptive neural networks and robust methods [6–11]. The proposed methods show good dynamical responses, but robustness in the presence of model dynamical uncertainties and system nonlinearities were not considered. Also, some of them suggest complex state feedback or high order dynamical controllers, which are not practical for industry practices.

Research on the LFC problem shows that the fuzzy proportional-integral (PI) controller is simpler and more applicable to remove the steady state error [12]. The fuzzy PI controller is known to give poor performance in the system transient response. In view of this, some authors proposed fuzzy proportional-integral-derivative (PID) methods to improve the performance of the fuzzy PI controller [13–15]. It should be pointed out that it requires a three-dimensional rule base. This problem makes the design process more difficult. In order to overcome this drawback and focus on the separated PD part from the integral part, this paper presents a multi-stage fuzzy (MSF) PID controller with a fuzzy switch. This is a form of behavior based control where the PD (proportional-derivative) controller becomes active only when certain conditions are met. The resulting structure is a controller using two dimensional inference engines (rule base) to perform reasonably the task of a three dimensional controller. The proposed method requires fewer resources to operate, and its role in the system response is more apparent, i.e. it is easier to understand the effect of a two dimensional controller than a three dimensional one [16–18]. This newly developed control strategy combines a fuzzy PD controller and an integral controller with a fuzzy switch. The fuzzy PD stage is employed to penalize fast change and large overshoots in the control input due to corresponding practical constraints. The integral stage is also used in order to get disturbance rejection and zero steady state error. Successful design of a rule based fuzzy control system depends on several factors such as the choice of the rule set, membership functions, inference mechanism and the defuzzification strategy. Of these factors, exact tuning of membership functions is more difficult in the proposed MSF controller because it is a computationally expensive combinatorial optimization problem. Usually, the tuning of membership functions is derived from human experts who have acquired their knowledge through experience. However, experts may not always be available. Even where available, extraction of an appropriate set of membership functions from the experts may be tedious, time consuming and process specific. Thus, optimization of membership functions tuning is an important and essential step toward the design of any successful fuzzy controllers. For this reason, a modified genetic algorithm (GA) is being used for tuning the membership functions in the proposed MSF controller to reduce the fuzzy system effort. Classical GAs are powerful search techniques to find the global optimal area. However, the global optimal value is not guaranteed using this method, and the speed of the algorithms convergence is extremely reduced too. To overcome this drawback, the hill climbing method is proposed to improve the speed of the algorithms convergence. Besides, the global optimal value is also guaranteed by this method.

To illustrate the effectiveness of the proposed method a three area restructured power system is considered as a test system. The results of the proposed genetic algorithms based MSF (GAMSF) controller are compared with the MSF [16] and classical fuzzy PID controller (FPID) [13] through some performance indices in the presence of large parametric uncertainties and system nonlinearities under various area load changes. The performance indices are chosen as the integral of the time multiplied absolute value of the error (ITAE) and the figure of demerit (FD). The simulation results show that the proposed controller not only achieves good robust performance for a wide range of system parameters and area load disturbances changes, even

### Nomenclature

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
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<tbody>
<tr>
<td>( F )</td>
<td>area frequency</td>
</tr>
<tr>
<td>( P_{\text{tie}} )</td>
<td>net tie line power flow</td>
</tr>
<tr>
<td>( P_T )</td>
<td>turbine power</td>
</tr>
<tr>
<td>( P_V )</td>
<td>governor valve position</td>
</tr>
<tr>
<td>( P_C )</td>
<td>governor set point</td>
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<td>ACE</td>
<td>area control error</td>
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<tr>
<td>( \Delta )</td>
<td>deviation from nominal value</td>
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<td>( K_P )</td>
<td>subsystem equivalent gain</td>
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<td>( T_P )</td>
<td>subsystem equivalent time constant</td>
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<tr>
<td>( T_T )</td>
<td>turbine time constant</td>
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<td>( T_H )</td>
<td>governor time constant</td>
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<tr>
<td>R</td>
<td>droop characteristic</td>
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<tr>
<td>B</td>
<td>frequency bias</td>
</tr>
<tr>
<td>( T_{ij} )</td>
<td>tie line synchronizing coefficient between areas ( i ) and ( j )</td>
</tr>
<tr>
<td>( P_d )</td>
<td>area load disturbance</td>
</tr>
<tr>
<td>( P_{\text{Lij}} )</td>
<td>contracted demand of Disco ( j ) in area ( i )</td>
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<tr>
<td>( P_{\text{ULij}} )</td>
<td>un-contracted demand of Disco ( j ) in area ( i )</td>
</tr>
<tr>
<td>( P_{\text{mij}} )</td>
<td>power generation of GENCO ( j ) in area ( i )</td>
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<tr>
<td>( P_{\text{Loc}} )</td>
<td>total local demand</td>
</tr>
<tr>
<td>( \eta )</td>
<td>area interface</td>
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<tr>
<td>( \zeta )</td>
<td>scheduled power tie line power flow deviation ( (\Delta P_{\text{tie,sch.}}) )</td>
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in the presence of generation rate constraints (GRC), but also it is superior to the MSF and FPID controllers. Moreover, the proposed control strategy does not require an accurate model of the plant and leads to a flexible controller with simple structure that is easy to implement. Thus, it is recommended to generate good quality and reliable electric energy in the real world complex power systems.

2. Description of generalized LFC scheme

In the restructured power systems, the vertically integrated utility (VIU) no longer exists. However, the common LFC goals, i.e., restoring the frequency and the net interchanges to their desired values for each control area, still remain [19,20]. A generalized dynamical model for a LFC scheme has been developed in Ref. [21] based on the possible contracts in the restructured environments.

This section gives a brief overview of this generalized model that uses all the information required in a VIU industry plus the contract data information. In the new structure, generation companies (GENCOs) may or may not participate in the LFC task and distribution companies (DISCOs) have the liberty to contract with any available GENCOs in their own or other areas. Thus, there can be various combinations of the possible contracted scenarios between DISCOs and GENCOs. The concept of an augmented generation participation matrix (AGPM) is introduced to express these possible contracts in the generalized model. The rows and columns of an AGPM are equal to the total number of GENCOs and DISCOs in the overall power system, respectively. For example, the AGPM structure for a large scale power system with $N$ control area is given by:

$$\text{AGPM} = \begin{bmatrix}
\text{AGPM}_{11} & \cdots & \text{AGPM}_{1N} \\
& \ddots & \\
\text{AGPM}_{N1} & \cdots & \text{AGPM}_{NN}
\end{bmatrix}$$

(1)

where

$$\text{AGPM}_{ij} = \begin{bmatrix}
gpf_{(s_i+1)(z_j+1)} & \cdots & gpf_{(s_i+1)(z_j+m_j)} \\
& \ddots & \\
gpf_{(s_i+n_i)(z_j+1)} & \cdots & gpf_{(s_i+n_i)(z_j+m_j)}
\end{bmatrix}$$

for $i,j=1, \ldots, N$ and $s_i = \sum_{k=1}^{i-1} n_k$, $z_j = \sum_{k=1}^{j-1} m_k$, $s_1 = z_1 = 0$.

In the above, $n_i$ and $m_i$ are the number of GENCOs and DISCOs, respectively, in area $i$ and gpf$_{ij}$ refers to ‘generation participation factor’ and shows the participation factor of GENCO $i$ in the total load following requirement of DISCO $j$ based on the possible contract. The sum of all entries in each column of an AGPM is unity.

To illustrate the effectiveness of the proposed control design and modeling strategy, a three control area power system is considered as a test system. It is assumed that each control area includes two GENCOs and two DISCOs.

A block diagram of the generalized LFC scheme for a three area restructured power system is shown in Fig. 1. The power system parameters are given in Tables 1 and 2.

The dashed lines show the demand signals based on the possible contracts between GENCOs and DISCOs, which carry information as to which GENCO has to follow a set of scheduled active power generation for a given period. The solid lines show the signals that are absent in the traditional LFC scheme. As there are many GENCOs in each area, the ACE signal has to be distributed among them due to their ACE participation factors.

$$d_i = \Delta P_{\text{Loc},i} + \Delta P_{\text{di}}, \quad \Delta P_{\text{Loc},i} = \sum_{j=1}^{m_i} \Delta P_{L_j,i},$$

(2)

$$\Delta P_{\text{di}} = \sum_{j=1}^{m_i} \Delta P_{L(j),j-i}$$

$$\eta_i = \sum_{j=k+1}^{N} T_{ij} \Delta f_j$$

$$\zeta_i = \Delta P_{\text{tie},i,\text{sch}} = \sum_{k=1}^{N} \Delta P_{\text{tie},i,k,\text{sch}}$$

$$\Delta P_{\text{tie},i,k,\text{sch}} = \sum_{j=1}^{m_j} \sum_{i=1}^{m_i} apf_{(s_i+1)(z_j+1)} \Delta P_{L(z_j+1)-i} - \sum_{j=1}^{m_j} \sum_{i=1}^{m_i} apf_{(s_i+1)(z_j+1)} \Delta P_{L(z_j+1)-i}$$

$$\Delta P_{\text{tie},i,\text{error}} = \Delta P_{\text{tie},i,\text{actual}} - \zeta_i$$

$$\rho_i = \begin{bmatrix}
\rho_{i1} & \cdots & \rho_{ik} & \cdots & \rho_{ni} \\
\end{bmatrix},$$

$$\rho_{li} = \sum_{j=1}^{m_i} \sum_{i=1}^{m_i} \rho_{ji} = \sum_{j=1}^{m_i} \sum_{i=1}^{m_i} \rho_{ji}$$

$$\Delta P_{m,k-i} = \rho_{li} + apf_{li} \Delta P_{di}, \quad k = 1, 2, \ldots, n_i$$

(7)

3. Classical fuzzy based controller design

Nowadays, fuzzy theory is used in almost all sectors of industry and science. One of them is power system control. Fuzzy logic control is one of the most successful areas in the application of fuzzy theory and is an excellent alternative to the conventional control methodology when the processes are too complex for analysis by conventional mathematical techniques [22,23]. Because of the complexity and multi-variable conditions of the power system, conventional control methods may not give satisfactory solutions. On the other hand, their robustness and reliability make fuzzy controllers useful for solving a wide range of control problems in power systems. In general, the application of fuzzy logic to PID control design for solution of the LFC problem can be classified in two major categories according to the way of their construction [14]:

1. A typical LFC is constructed as a set of heuristic control rules, and the control signal is directly deduced from the knowledge base.
2. The gains of the conventional PID controller are tuned on line in terms of the knowledge base and fuzzy inference, and then, the conventional PID controller generates the control signal.

Fig. 2 shows the block diagram of a classical fuzzy type controller to solve the LFC problem for each control area (Fig. 1).


Fig. 2. The classical FPID controller design problem.

Table 1
GENCOs parameter

<table>
<thead>
<tr>
<th>MVAbase (1000 MW) parameter</th>
<th>GENCOs (k in area i)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1–1</td>
</tr>
<tr>
<td>Rate (MW)</td>
<td>1000</td>
</tr>
<tr>
<td>$T_I$ (s)</td>
<td>0.32</td>
</tr>
<tr>
<td>$T_G$ (s)</td>
<td>0.06</td>
</tr>
<tr>
<td>$\delta$ (Hz/pu)</td>
<td>2.4</td>
</tr>
<tr>
<td>$s$</td>
<td>0.5</td>
</tr>
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</table>

Table 2
Control area parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Area-1</th>
<th>Area-2</th>
<th>Area-3</th>
</tr>
</thead>
<tbody>
<tr>
<td>$K_P$ (Hz/pu)</td>
<td>120</td>
<td>120</td>
<td>125</td>
</tr>
<tr>
<td>$T_P$ (s)</td>
<td>20</td>
<td>25</td>
<td>20</td>
</tr>
<tr>
<td>$B$ (pu/Hz)</td>
<td>0.4250</td>
<td>0.3966</td>
<td>0.3522</td>
</tr>
<tr>
<td>$T_i$ (pu/Hz)</td>
<td>$T_{12} = 0.245$, $T_{11} = 0.212$</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Based on AGPM

Area 1

Area 2

Area 3

Fig. 1. Generalized LFC Scheme in a restructured environment.
In the design of a fuzzy logic controller, there are five parts of the fuzzy inference process:

1. Fuzzification of the input variables.
2. Application of the fuzzy operator (AND or OR) in the antecedent.
3. Implication from the antecedent to the consequent.
4. Aggregation of the consequents across the rules.
5. Defuzzification.

According to the control methodology as given in Ref. [16], a classical fuzzy PID controller for each of the three areas is designed. The proposed controller is a two level controller. The first level is a fuzzy network and the second level is a PID controller. In this strategy, the gains $K_p$, $K_i$, and $K_d$, as given by Eq. (9), are tuned on line in terms of the knowledge base and fuzzy inference, and then, the conventional PID controller generates the control signal, which applies to the governor set point in each area as follows:

\[ u_i = K_p \text{ACE}_i(t) + K_i \int_0^t \text{ACE}_i(t) \, dt + K_d \Delta \text{CE}(t) \]  

(9)

The membership function sets and the appropriate rules for the above control strategy are given in Ref. [16]. More details are given in Refs. [13,16] about the design processes of this control method.

4. GA based MSF controller design scheme

GAs are search algorithms based on the mechanism of natural selection and natural genetics that operate without knowledge of the task domain and utilize only the fitness of evaluated individuals. In general, reproduction, crossover and mutation are the three basic operators of GAs. They can be considered as a general purpose optimization method and have been successfully applied to search and optimization [24,25].

During evolution, GAs require only information of the quality of the fitness value produced by each parameter set. This differs from many optimization methods requiring derivative information or complete knowledge of the problem structure and parameter. Hence, the GA is more suitable to deal with the problem of the lack of experience or knowledge than other searching methods, in particular, when the phenomena being analyzed are describable in terms of rules for action and learning processes [26].

In this paper, a modified GA based MSF controller is proposed for solution of the LFC problem. The motivation of using the proposed MSF controller is to take into account large parametric uncertainties and system nonlinearities while minimizing area load disturbances. As the MSF controller is elaborately explained in the author’s previous paper [16], here we only point out its salient features briefly. This control strategy combines a fuzzy PD controller and an integral controller with a fuzzy switch. The fuzzy PD stage is employed to penalize fast change and large overshoots in the control input due to corresponding practical constraints. The integral stage is also used in order to get disturbance rejection and zero steady state error.

It should be noted that the exact tuning of membership functions in the MSF control strategy is very important to achieve the desired level of system robust performance because it is a computationally expensive, combinatorial optimization problem. Usually, tuning of membership functions are derived from human experts who have acquired their knowledge through experience. However, experts may not always be available. Even where available, extraction of an appropriate set of membership functions from the expert may be tedious, time consuming and process specific. In order to overcome this drawback and reduce fuzzy system effort and cost, a modified GA is being used to tune optimally the membership functions in the proposed MSF controller. Fig. 3 shows the structure of the proposed GAMSF controller for solution of the LFC problem. In the multi-stage structure, input values are converted to truth value vectors and applied to their respective rule base. The output truth value vectors are not defuzzified to crisp values as with a single stage fuzzy logic controller but are passed on to the next stage as a truth value vector. This allows for a more flexible and accurate representation of the system state.

![Fig. 3. Structure of the proposed GAMSF control strategy.](image-url)
value vector input. The darkened lines in Fig. 3 indicate truth value vectors.

In this effort, all membership functions are defined as triangular partitions with seven segments from −1 to 1. Zero (ZO) is the center membership function, which is centered at zero. The partitions are also symmetric about the ZO membership function as shown in Fig. 4. The remaining parts of the partition are negative big (NB), negative medium (NM), negative small (NS), positive small (PS), positive medium (PM) and positive big (PB).

There are two rule bases used in the MSF controller. The first is called the PD rule base as it operates on truth vectors from the error (\(e\)) and change in error (\(\Delta e\)) inputs. A typical PD rule base for the fuzzy logic controller is given in Table 3. This rule base responds to a negative input from either error (\(e\)) or change in error (\(\Delta e\)) with a negative value, thus driving the system toward the commanded optimum value. The partitions are also symmetric about the ZO (ZO) is the center membership function, which is centered at zero. The partitions are also symmetric about the ZO.

Table 3 shows a PID switch rule base. This rule base is designed to pass through the PD input if the PD input is not in the zero fuzzy set. If the PD input is in the zero fuzzy set, then the PID switch rule base passes the integral error values (\(\int e\)). This rule base operates as the behavior switch, giving control to PD feedback when the system is in motion and reverting to integral feedback to remove the steady state error when the system is no longer moving. The operation used to determine the consequence value at the intersection of two input fuzzy values is given as:

\[
c_{ij} = \Pi(a_i b_j), \quad \text{with } i, j = 1, 2, \ldots, N_m
\]

where \(a_i\) is the membership value of the \(i\)th fuzzy set for a given \(e\) input, and \(b_j\) is likewise for a given \(\Delta e\) input. The operator used to determine the membership value of the \(k\)th consequence set is:

\[
C_k = \sum C_{i,j}, \quad \text{with } i, j = 1, 2, \ldots, N_m
\]

The defuzzification uses the weighted average method where \(C_k\) is the peak point of the \(k\)th output fuzzy membership function.

\[
d = \sum C_k \Delta C_k / \sum C_k, \quad \text{with } k = 1, 2, \ldots, N_m\text{(sets in output point)}
\]

4.1. Tuning of membership functions by modified GA

In the proposed GAMSF controller, we must tune the linguistic hedge combinations, which are difficult to extracted from human experience and knowledge. To acquire an optimal combination, we adopt the modified GAs as the search method. In this work, the GA module works off line. The classical GA searches for the optimal or near optimal linguistic hedge combination according to the controlled plants. According to Fig. 4, for exact tuning of the used membership functions in the proposed method, we must find the optimal value for the \(a\) and \(b\) parameters, where \(0 < a < b < 1\).

Among all the various GAs, the classical GA is the simplest one without loss of efficiency. In this study, we adopted a modified GA to improve the speed of convergence and find the global optimum value of the fitness function. Fig. 5 shows the flow chart of the modified GA approach for optimization. In this algorithm, the classical GA is used to find the near optimal global value, and then, the proposed hill climbing method is used to find the global optimum value.

Before proceeding with the GA approach, there are two preliminaries to be finished.

1. **Definition of suitable coding**: one of the most attractive problems in GAs is coding the solution space. According to Fig. 4, there are two parameters to tune the membership functions (\(a\) and \(b\) parameters). Thus, the order of parameters is coded into the chromosome (individual). A chromosome represents a candidate solution of the problem. In this method, a solution candidate is expressed by binary coding. Consequently, the \(a\) and \(b\) parameters for the ACE, \(\Delta ACE\), \(\int ACE\) and output membership functions are expressed in terms of strings consisting of 0 and 1 as shown in Fig. 6. From this figure, it can be seen that the length of the chromo-
some is 40 genes (bits). The solution candidate expressed by a string is called an individual and a set of individuals is called a population.

(2) **Choice of fitness functions**: the second preliminary to be finished is choosing the problem dependent fitness function. Different fitness functions promote different GA behaviors, which generate fitness values providing a performance measure of the problem considered. In the present study, an evaluation of $f(\text{ITAE})$ is an alternative to the conventional maximization of fitness function, which is defined as follows:

$$ f(\text{ITAE}) = \frac{1}{1 + \text{MSE}(\text{ITAE})} $$

where

$$ \text{MSE}(\text{ITAE}) = \sqrt{\frac{\sum_{i=1}^{3} \text{ITAE}_i}{3}}. $$

$$ \text{ITAE}_i = 100 \int_0^t |\text{ACE}_i| \, dt $$

After deciding these two preliminaries, we should choose the genetic operators. This algorithm consists of elitism selection and three kinds of genetic operators, which are selection, crossover and mutation to create the new generation.

(1) **Selection**: Selection chooses the individuals in the population as parent individuals to create offspring for the next generation, whose purpose is to emphasize the fitter individuals in the population in hopes that their offspring will, in turn, have even higher fitness. In this work, roulette wheel selection is adopted.

(2) **Crossover**: Instead of the single point crossover, we adopt the two point crossover. For example, the parent individuals $h_1$ and $h_2$ given to be crossed over at the points $k$ and $l$ with the crossover probability $P_c$ results in the new offspring $h'_1$ and $h'_2$ that are expressed as:

$$ \text{ACE}_i, \Delta\text{ACE}_i, \int\text{ACE}_i, \text{Output} $$

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Fig. 5. Modified GA approach for exact tuning for optimal membership functions.

Fig. 6. String encoding membership function.
\( h'_1 = \begin{cases} h_2 & k < i < l \\ h_1 & \text{otherwise} \end{cases} \)
\( h'_2 = \begin{cases} h_1 & k < i < l \\ h_2 & \text{otherwise} \end{cases} \)

(3) **Mutation:** A position of each gene with probability \( P_m \), which is a possible candidate for mutation, is selected randomly, and then, the value of the gene, 0 or 1, is changed to 1 or 0, respectively.

(4) **Elitism:** Elitism guarantees that the best string individual survives until the last generation. Among parents and their children that are generated by crossover and mutation, individuals that have the best fitness function only survive to the next generation. The size of individuals in the next generation is the same as the initial population size.

In order to acquire better performance, several parameters for GAs should be set appropriately. In this work, these parameters are listed in Table 5.

Genetic algorithms are powerful search techniques for optimization, but some well known disadvantages in GAs are poor convergence of the classical GA near the global optimum and convergence to a sub-optimum. In order to overcome these drawbacks, the following procedures are being used in the proposed modified GA:

1. In each iteration, the probability of mutation \( (P_m) \) is changed according to Fig. 5 if the fitness function value does not improve in comparison with the previous generation. This method guarantees algorithm convergence to the near optimum solution.
2. In order to overcome the poor convergence of the classical GA to the global optimum value and improve the convergence speed, the result of the classical GA is being used for the hill climbing method as initial conditions. Fig. 7 shows a flow chart of the proposed hill climbing method.

Here, the modified GA evolution procedure is applied to tune exactly the membership functions of the proposed MSF controller for solution of the LFC problem. After 34 generations, we can obtain the optimum hedge linguistic terms of the membership functions. Fig. 8 shows the convergence of the classical GA. The results of membership function set values are listed in Table 6. The fitness value by the classical GA is 0.10237, which is improved to 0.11241 by the proposed hill climbing method.

5. **Simulation results**

In the simulation study, the linear model of the turbine \( \Delta P_{V_i}/\Delta P_{T_k} \) in Fig. 1 is replaced by the nonlinear model of

<table>
<thead>
<tr>
<th>GA set parameters</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of generation</td>
<td>100</td>
</tr>
<tr>
<td>Population size</td>
<td>20</td>
</tr>
<tr>
<td>Crossover rate</td>
<td>0.97</td>
</tr>
<tr>
<td>Mutation rate</td>
<td>0.08</td>
</tr>
</tbody>
</table>

![Flow chart](image_url)
Fig. 9 (with ±0.03 limit). This is to take the GRC into account, i.e., the practical limit on the rate of change in the generating power of each GENCO. The results in Refs. [16,21] indicated that the GRC would influence the dynamic responses of the system significantly and lead to larger overshoot and longer settling time.

The proposed MSF-PID controller is applied for each control area of the restructured power system as shown in Fig. 1. To illustrate the robustness of the proposed control strategy against parametric uncertainties and contract variations, simulations are conducted for three scenarios of possible contracts under various operating conditions and large load demands. The performance of the proposed MSF-PID controllers is compared with those of the MSF and FPID controllers.

### 5.1. Scenario 1: Poolco based transactions

In this scenario, the GENCOs participate only in the load following control of their areas. It is assumed that a large step load 0.1 pu is demanded by each DISCO in areas 1 and 2. Assume that a case of Poolco based contracts between DISCOs and available GENCOs is simulated based on the following AGPM. It is noted that the GENCOs of area 3 do not participate in the LFC task.

\[
\text{AGPM} = \begin{bmatrix}
0.6 & 0.5 & 0 & 0 & 0 & 0 \\
0.4 & 0.5 & 0 & 0 & 0 & 0 \\
0 & 0 & 0.5 & 0.5 & 0 & 0 \\
0 & 0 & 0 & 0.5 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]

The frequency deviation of the two areas, the GENCO’s power change and tie line power flow with 25% decrease in system parameters are depicted in Figs. 10 and 11. Using the proposed method, the frequency deviation of all areas and the tie line power are quickly driven back to zero and have small overshoots (Fig. 10). Since there are no contracts between areas, the scheduled steady state power flows, Eq. (5), over the tie line are zero. Also, the actual generated powers of the GENCOs, according to Eq. (8), properly converge to the desired value in the steady state case, i.e.:

\[
\Delta P_{M,1-1} = 0.11 \text{ pu MW, } \Delta P_{M,2-1} = 0.09 \text{ pu MW, } \\
\Delta P_{M,1-2} = 0.1 \text{ pu MW, } \Delta P_{M,2-2} = 0.1 \text{ pu MW}
\]

### 5.2. Scenario 2: Combination of poolco and bilateral based transactions

In this scenario, DISCOs have the freedom to have a contract with any GENCO in their or any other area. Consider that all the DISCOs contract with the available GENCOs for power as per the following AGPM. All GENCOs participate in the LFC task. GENCO 1 in area 2 and GENCO 2 in area 3 only participate for perform-

---

### Table 6

<table>
<thead>
<tr>
<th>Membership function</th>
<th>Classical GA</th>
<th>Modified GA</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a)</td>
<td>0.7896</td>
<td>0.7097</td>
</tr>
<tr>
<td>(b)</td>
<td>0.9437</td>
<td>0.9677</td>
</tr>
<tr>
<td>(a)</td>
<td>0.3994</td>
<td>0.4194</td>
</tr>
<tr>
<td>(b)</td>
<td>0.6106</td>
<td>0.5806</td>
</tr>
<tr>
<td>(\Delta \text{ACE}_i)</td>
<td>0.5413</td>
<td>0.4516</td>
</tr>
<tr>
<td>(f \text{ACE})</td>
<td>0.8152</td>
<td>0.7742</td>
</tr>
<tr>
<td>Output</td>
<td>0.4513</td>
<td>0.4742</td>
</tr>
</tbody>
</table>

---

![Fig. 8. Classical GA convergence.](image)

![Fig. 9. Nonlinear turbine model with GRC.](image)
ing the LFC task in their areas, while the other GEN-COs track the load demand in their area and/or other areas.

\[
AGPM = \begin{bmatrix}
0.25 & 0 & 0.25 & 0 & 0.5 & 0 \\
0.5 & 0.25 & 0 & 0.25 & 0 & 0 \\
0 & 0.5 & 0.25 & 0 & 0 & 0 \\
0.25 & 0 & 0.5 & 0.75 & 0 & 0 \\
0 & 0.25 & 0 & 0 & 0.5 & 0 \\
0 & 0 & 0 & 0 & 0 & 1
\end{bmatrix}
\]

It is assumed that a large step load 0.1 pu MW is demanded by each DISCO in all areas. The power system responses with 25% increase in system parameters are shown in Figs. 12 and 13. Using the proposed method, the frequency deviations of all the areas are quickly driven back to zero and have small settling times. Also, the tie line power flow properly converges to the specified value of Eq. (5) in the steady state case (Fig. 12), i.e., \(\Delta P_{\text{tie}21, \text{sch}} = 0.025 \text{ pu} \) and \(\Delta P_{\text{tie}31, \text{sch}} = -0.025 \text{ pu} \). As shown in Fig. 13, the actual generated powers of the GENCOs properly reach the desired values in the steady state case, as given by Eq. (8), i.e.:

\[
\Delta P_{\text{M,1-1}} = 0.1 \text{ pu MW}, \quad \Delta P_{\text{M,2-1}} = 0.1 \text{ pu MW} \\
\Delta P_{\text{M,1-2}} = 0.075 \text{ pu MW}, \quad \Delta P_{\text{M,2-2}} = 0.15 \text{ pu MW} \\
\Delta P_{\text{M,1-3}} = 0.075 \text{ pu MW}, \quad \Delta P_{\text{M,2-3}} = 0.1 \text{ pu MW}
\]

5.3. Scenario 3: Contract violation

In this Scenario, it may happen that a Disco violates a contract by demanding more power than that specified in the contract. This excess power must be reflected as a local load of the area but not as the contracted demand to be taken up by the GENCOs in the same area. Consider scenario 2 again with the modifications of excess power as: DISCO\(_{1-1} = 0.06 \text{ pu MW}, \) DISCO\(_{2-1} = 0.00 \text{ pu MW}, \) DISCO\(_{1-2} = 0.00 \text{ pu MW}, \) DISCO\(_{2-2} = 0.05 \text{ pu MW}, \) DISCO\(_{1-3} = 0.02 \text{ pu MW} \) and DISCO\(_{2-3} = 0.02 \text{ pu MW}. \) The total local load in areas 1 and 2 are computed as:
The power system responses in this scenario with 25% decrease in system parameters are shown in Figs. 14 and 15. Using the proposed method, the frequency deviation of all the areas and the tie line power flows are quickly driven back to zero and have small settling times. Also, the tie line power flows properly converge to the specified values, Eq. (5), in the steady state, i.e.: $\Delta P_{tie1,sch} = 0.025$ and $\Delta P_{tie31,sch} = -0.025$ pu MW. Based on Eq. (8), the

\[
\Delta P_{Loc1} = (0.1 + 0.06) + 0.1 = 0.26,
\]
\[
\Delta P_{Loc2} = 0.1 + (0.1 + 0.05) = 0.25,
\]
\[
\Delta P_{Loc31} = (0.1 + 0.02) + (0.1 + 0.02) = 0.24.
\]
actual generated powers of GENCOs in all areas are given by:
\[ \Delta P_{M,1-1} = 0.13 \text{ pu MW}, \quad \Delta P_{M,2-1} = 0.13 \text{ pu MW} \]
\[ \Delta P_{M,1-2} = 0.1 \text{ pu MW}, \quad \Delta P_{M,2-2} = 0.175 \text{ pu MW} \]
\[ \Delta P_{M,1-3} = 0.099 \text{ pu MW}, \quad \Delta P_{M,2-3} = 0.116 \text{ pu MW} \]

As shown in Fig. 15, the actual generated powers of the GENCOs properly reach the desired values using the proposed control strategy.

To demonstrate the performance robustness of the proposed method, the integral of the time multiplied absolute value of the error (ITAE) and figure of demerit (FD) based on the system performance characteristics are being used as:

![Fig. 14. Deviation of frequency and tie lines power flows; solid (GAMSF), dashed (MSF) and dotted (FPID).](image1)

![Fig. 15. GENCOs power changes; solid (GAMSF), dashed (MSF) and dotted (FPID).](image2)
\[
\text{ITAE} = \int_0^{10} t(\text{ACE}_1(t) + |\text{ACE}_2(t)| + |\text{ACE}_3(t)|)dt
\]
(15)

\[
\text{FD} = (\text{OS} \times 10)^2 + (\text{US} \times 4)^2 + (T_s \times 0.3)^2
\]
(16)

where Overshoot (OS), Undershoot (US) and settling time (for the 3% band of the total load demand in area 1) of the frequency deviation of area 1 is considered for evaluation of the FD. The values of ITAE and FD are calculated for the above scenarios, whereas the system parameters are varied from -25% to 25% of the nominal values. Figs. 16–18 show the values of ITAE and FD for the operation conditions under scenarios 1–3, respectively.

The above results show that in comparison with both the FPID and MSF controllers, the system performance...
is significantly improved by the GAMSF controller designed in this paper against the plant parameters changes.

6. Conclusions

In this paper, a new robust GA based MSF controller is proposed for solution of the LFC problem in restructured power systems. This control strategy was chosen because of the increasing complexity and changing structure of the power systems. This newly developed control strategy combines the advantages of the fuzzy PD and integral controllers for achieving the desired level of robust performance, such as precise reference frequency tracking and disturbance attenuation under a wide range of plant parameters and area load changes. It should be noted that to achieve the desired level of robust performance, exact tuning of the membership functions is very important in the proposed method. Thus, to reduce fuzzy system effort and increase cost saving, a modified GA has been used to tune the membership functions. In this work, the classical GA works offline and is used to find the near optimal linguistic hedge of membership functions. In order to overcome the poor convergence of the classical GA and improve the convergence speed, the result of the classical GA is used for the hill climbing method as initial conditions. The proposed method can guarantee the optimum value of the fitness function.

The salient feature of the proposed method is that it does not require an accurate model of the LFC problem, and the design process is less demanding than that of the other fuzzy PID controllers. Moreover, it has simple structure and is easy to implement, which ideally useful for the real world power systems. The proposed GAMSF controller was tested on a three area restructured power system to demonstrate its robust performance under three possible contracted scenarios for different operating conditions. Simulation results show that the proposed control strategy is very effective and achieves good robust performance against parametric uncertainties, load changes and disturbances even in the presence of GRC. The system performance characteristics in terms of ‘ITAE’ and ‘FD’ indices reveal that the proposed GAMSF is a promising control scheme for solution of the LFC problem and is superior to the MSF and FPI controllers. Thus, it is recommended to generate good quality and reliable electric energy in restructured power systems.

References


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