# Fuzzy Logic-Based Load-Frequency Control Concerning High Penetration of Wind Turbines

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# Fuzzy Logic-Based Load-Frequency Control Concerning High Penetration of Wind Turbines

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***Abstract*—Load-frequency control (LFC) in interconnected power systems is undergoing fundamental changes due to rapidly growing amount of wind turbines, and emerging of new types of power generation/consumption technologies. The infrastructure of modern LFC systems should be able to handle complex multiobjective regulation optimization problems characterized by a high degree of diversification in policies, and widely distribution in demand and supply sources to ensure that the LFC systems are capable to maintain generation-load balance, following serious disturbances. Wind power fluctuations impose additional power imbalance to the power system and cause frequency deviation from the nominal value. This paper addresses a new decentralized fuzzy logic-based LFC schemes for simultaneous minimization of system frequency deviation and tie-line power changes, which is required for successful operation of interconnected power systems in the presence of high-penetration wind power. In order to obtain an optimal performance, the particle swarm optimization technique is used to determine membership functions parameters. The physical and engineering aspects have been fully considered, and to demonstrate effectiveness of the proposed control scheme, a time domain simulation is performed on the standard 39-bus test system. The results are compared with conventional LFC design for serious load disturbance and various rates of wind power penetrations.**

***Index Terms*—Fuzzy control, load-frequency control, particle swarm optimization, wind power generation.**



## I. Introduction

CURRENTLY, wind is the fastest growing and most widely utilized renewable energy technology in power systems. The wind turbine generators have attracted an accelerated attention in recent years. In the end of 2008, wind power installed capacity was reached more than 120.2 GW worldwide and by the end of 2009, this value has grown up to 158.5 GW, which represents a growth of 31.7% in a year [1]. Nowadays, due to the interconnection of more distributed generators, especially wind turbines, the electric power industry has become more complicated than ever. Since, the primary energy source (wind) cannot be stored and is uncontrollable, the controllability and availability of wind power significantly differs from conventional power generation [2]. In most power systems, the output power of wind turbine generators varies with wind speed fluctuation, this fluctuation results into frequency variation [3]. Some reports have recently addressed the power system frequency control issue, in the presence of wind turbines [2], [4]–[9].

Load-frequency control (LFC) synthesis in power systems has a long history and its literature is voluminous. The preliminary LFC schemes have evolved over the past decades, and interest continues in proposing new intelligent LFC approaches with an improved ability to maintain tie-line power flow and system frequency close to specified values. In case of a high penetration wind power, the power system frequency regulation can be affected due to wind power fluctuation. This leads to imbalance between power generation and power demand, and as a result, frequency will deviate from its nominal value. Significant frequency deviations may cause under/over frequency relay operations and finally disconnect some parts of system loads and generations. The impact of wind power generation on system frequency response and LFC mechanism is discussed in [2] and [10].

The conventional LFC designs are usually suitable for working at specific operating points, and they are not more efficient for modern power systems, considering increasing size, changing structure, emerging renewable energy sources, and new uncertainties. Most of conventional LFC synthesis methodologies provide model-based controllers that are difficult to use for large-scale power systems with nonlinearities, and uncertain parameters. On the other hand, most of applied linear modern/robust control techniques to the LFC problem suggest complex control structure with high-order dynamic controllers, which are not practical for industry practices [11]. Therefore, it is expected that using intelligent LFC schemes in new environment to be more adaptive/flexible than conventional ones, and is going to become an appealing approach. Over the years, several intelligent control techniques are used for the frequency regulation/LFC issue in the power systems; however, there are just few reports on the intelligent frequency control design in the presence of wind power units.

Recently, following the advent of modern intelligent methods, such as artificial neural networks, fuzzy logic, multiagent systems, genetic algorithms, expert systems, simulated annealing, tabu search, ant colony optimization, and hybrid intelligent techniques, some new potentials and powerful solutions for LFC synthesis have arisen [12]. The human and

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nature ability to control complex organisms has encouraged researchers to pattern controls on human/nature responses, fuzzy behaviors, and neural network systems. Since all of developed artificial intelligent techniques are usually dependent on knowledge extracted from environment and available data, the *knowledge management* plays pivotal role in the LFC synthesis procedures.

Nowadays, fuzzy logic because of simplicity, robustness, and reliability is used in almost all fields of science and technology, including solving a wide range of control problems in power system control and operation. Unlike the traditional control theorems, which are essentially based on the linearized mathematical models of the controlled systems, the fuzzy control methodology tries to establish the controller directly based on the measurements, long-term experiences, and the knowledge of domain experts/operators.

Several studies have been already reported for the fuzzy logic-based LFC design schemes in the literature [13]–[19], some differing significantly from each other by the number and type of inputs and outputs, or less significantly by the number and type of input and output fuzzy sets and their membership functions, or by the type of control rules, inference engine, and the defuzzification method. However, all reported LFC designs have used conventional simplified linear models, without considering the integration of wind turbines or other types of renewable energy sources (RESs).

This paper addresses a new intelligent methodology using a combination of fuzzy logic and particle swarm optimization (PSO) techniques to satisfy LFC objectives concerning the integration of wind power units. The PSO technique is used to find optimal values for membership functions parameters of the fuzzy logic controllers. The proposed LFC scheme offers many benefits for the large-scale and complex power system due to emerging numerous distributed generators and RESs, which the classical and nonflexible LFC structures may not be applicable to provide a desirable performance over a wide range of operating conditions. In order to investigate the efficiency of the proposed control strategy, a computer simulation has been conducted for the standard 39-bus 10-generator test system, including three wind farms, in MATLAB SimPower environment. The obtained results are compared with the conventional LFC design.

## II. LFC with Wind Farms

The impact of wind farms on the dynamic behavior of power system may cause a different system frequency response to a disturbance event. Since, the system inertia determines the sensitivity of overall system frequency, it plays an important role in this consideration. The lower system inertia leads to faster changes in the system frequency following a load-generation imbalance. The addition of synchronous wind generation to a power system intrinsically increases the system inertial response [2], [11].

The impact of wind farms on power system inertia is a key factor in investigating the power system LFC behavior in the presence of high penetration of wind power generation. To analyze the additional variation caused by wind turbines, the total effect is important, and every change in wind power output does not need to be matched one for one by a change in another generating unit moving in the opposite direction. However, the slow wind power fluctuation dynamics and total average power variation negatively contribute to the power imbalance and frequency deviation, which should be taken into account in the well-known LFC control scheme.

The conventional LFC model is well discussed in [11] and [20]. To generalize the conventional model, the updated area control error (ACE) signal should represent the impacts of wind power on the scheduled flow over the tie-lines. The ACE signal is traditionally defined as a linear combination of frequency and tie-line power changes [20] as follows:

$$\mathrm{ACE} = \beta\Delta f + \Delta P_{\mathrm{tie}} \tag{1}$$

where the $\Delta f$ is frequency deviation, the $\beta$ is frequency bias, and the $\Delta P_{\mathrm{tie}}$ is the difference between the actual (act) and scheduled (sched) power flows for a given area with $m$ tie-lines as follows:

$$\Delta P_{\mathrm{tie}} = \sum_{j=1}^{m}(P_{\mathrm{tie,act}\ j} - P_{\mathrm{tie,sched}\ j}). \tag{2}$$

For a considerable amount of wind ($W$) power, its impact must be also considered with conventional ($C$) power flow in the overall area tie-line power. Therefore, the updated $\Delta P_{\mathrm{tie}}$ can be expressed as follows:

$$\begin{aligned}\Delta P_{\mathrm{tie}} &= \Delta P_{\mathrm{tie-}C} + \Delta P_{\mathrm{tie-}W}\\ &= \sum_{j=1}^{m}(P_{\mathrm{tie}-C,\mathrm{act}\ j} - P_{\mathrm{tie}-C,\mathrm{sched}\ j})\\ &+ \sum_{j=1}^{m}(P_{\mathrm{tie}-W,\mathrm{act}\ j} - P_{\mathrm{tie}-W,\mathrm{estim}\ j}).\end{aligned} \tag{3}$$

Using (1) and (3), an updated ACE signal can be completed as follows:

$$\begin{aligned}\mathrm{ACE} = \beta\Delta f &+ \sum_{j=1}^{m}(P_{\mathrm{tie}-C,\mathrm{act}\ j} - P_{\mathrm{tie}-C,\mathrm{sched}\ j})\\ &+ \sum_{j=1}^{m}(P_{\mathrm{tie}-W,\mathrm{act}\ j} - P_{\mathrm{tie}-W,\mathrm{estim}\ j})\end{aligned} \tag{4}$$

where $P_{\mathrm{tie}-C,\mathrm{act}}$, $P_{\mathrm{tie}-C,\mathrm{sched}}$, $P_{\mathrm{tie}-W,\mathrm{act}}$, and $P_{\mathrm{tie}-W,\mathrm{estim}}$ are actual conventional tie-line power, scheduled conventional tie-line power, actual wind tie-line power, and scheduled wind tie-line power, respectively.

## III. Fuzzy Logic-Based LFC Scheme

A general scheme for fuzzy logic-based LFC system is given in Fig. 1. As shown, the fuzzy controller has four blocks. Crisp input information (usually measured ACE or frequency deviation) from the control area is converted into fuzzy values for each input fuzzy set with the fuzzification block. The universe of discourse of the input variables determines the required scaling/normalizing for correct per-unit operation.

The inference mechanism determines how the fuzzy logic operations are performed, and together with the knowledge

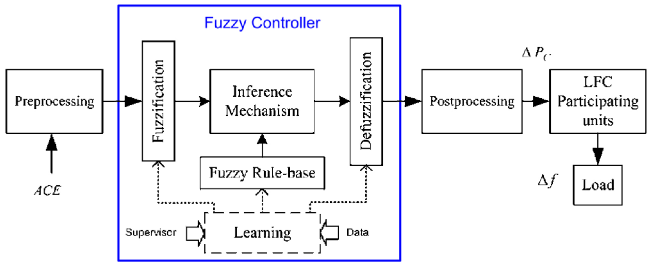


Fig. 1. General scheme for fuzzy logic-based LFC.

base determine the outputs of each fuzzy IF-THEN rules. Those are combined and converted to crispy values with the defuzzification block. The output crisp value can be calculated by the center of gravity or the weighted average; then, the scaled output as control signal is applied to the generating units.

Generally, a controller design based on fuzzy logic for a dynamical system involves the following four main steps.

Step 1) Understanding of the system dynamic behavior and characteristics. Define the states and input/output control variables and their variation ranges.

Step 2) Identify appropriate fuzzy sets and membership functions. Create the degree of fuzzy membership function for each input/output variable and complete fuzzification.

Step 3) Define a suitable inference engine. Construct the fuzzy rule base, using the control rules that the system will operate under. Decide how the action will be executed by assigning strengths to the rules.

Step 4) Determine defuzzification method. Combine the rules and defuzzify the output.

Consistent with the LFC design, the first step of fuzzy controller design is to choose the correct input signals to the LFC. The ACE and its derivative are usually chosen as inputs of the fuzzy controller. These two signals are then used as rule-antecedent (IF-part) in the formation of rule base, and the control output is used to represent the contents of the rule-consequent (THEN-part) in performing of rule base.

*Normalization* or scale transformation which maps the physical values of the current system state variables into a normalized universe of discourse should be properly considered. This action is also needed to map the normalized value of control output variables into its physical domain (denormalization output). The normalization can be obtained by dividing each crisp input on the upper boundary value for the associated universe.

In real world, many phenomena and measures are not crisp and deterministic. *Fuzzification* plays an important role in dealing with uncertain information, which might be objective or subjective in nature. The fuzzification block in the fuzzy controller represents the process of making crisp quantity into fuzzy. In fact, the fuzzifier converts the crisp input to a linguistic variable using the membership functions stored in the fuzzy knowledge base. Fuzzines in a fuzzy set is characterized by the *membership functions*. Using suitable membership functions, the ranges of input and output variables are assigned with

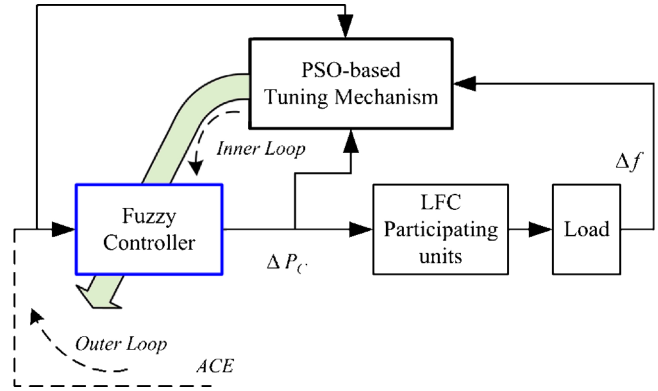


Fig. 2. Proposed scheme for adaptive fuzzy logic LFC.

linguistic variables. These variables transform the numerical values of the input of the fuzzy controller to fuzzy quantities. These linguistic variables specify the quality of the control. Triangular, trapezoid, and Gaussian are more common membership functions to use in fuzzy control systems.

*Knowledge rule base* consists of information storage for linguistic variables definitions (database), and fuzzy rules (control base). The concepts associated with a database are used to characterize fuzzy control rules and a fuzzy data manipulation in fuzzy logic controller. A lookup table is made based on discrete universes that defines the output of a controller for all possible combinations of the input signals. A fuzzy system is characterized by a set of linguistic statements in the form of "IF-THEN" rules. Fuzzy conditional statements make the rules or the rule set of the fuzzy controller. Finally, the *inference engine* uses the IF-THEN rules to convert the fuzzy input to the fuzzy output.

On the other hand, defuzzifier converts the fuzzy output of the inference engine to crisp using membership functions analogous to the ones used by the fuzzifier. For the defuzzification process, commonly center of sums, mean-max, weighted average, and centroid methods are employed to defuzzify the fuzzy incremental control law.

## IV. Proposed Intelligent LFC Scheme

To provide an adaptive and self-tuning fuzzy logic-based LFC system, the parameters of fuzzy logic controller (membership functions) can be adjusted using an external tuning mechanism. In this case, the adaptive fuzzy controller has a distinct architecture consisting of two loops: an inner control loop, which is the basic feedback loop, and an outer loop, which adjusts the parameters of the controller. The proposed control framework is shown in Fig. 2. Here, the PSO technique is used to perform the mentioned tuning mechanism.

In each control area, the PSO technique is used for tuning of fuzzy system's membership function parameters in the supplementary frequency control loop to improve the overall control performance.

### A. PSO Mechanism

The PSO is a population-based stochastic optimization technique. It belongs to the class of direct search methods that can be used to find a solution to an optimization problem in a search space. The PSO originally has been presented based on social behavior of bird flocking, fish schooling, and swarming theory [21], [22]. In the PSO method, a swarm consists of a set of individuals, with each individual specified by *position* and *velocity* vectors $(x_i(t), v_i(t))$ at each time or iteration. Each individual is named as a "*particle*" and the position of every particle represents a potential solution to the under study optimization problem. In an $n$-dimensional solution space, each particle is treated as a $n$-dimensional space vector and the position of the $i$th particle is presented by $v_i = (x_{i1}, x_{i2}, \ldots, x_{\text{in}})$; then it flies to a new position by velocity represented by $v_i = (v_{i1}, v_{i2}, \ldots, v_{\text{in}})$. The best position for $i$th particle represented by $p_{\text{best},i} = (p_{\text{best},i1}, p_{\text{best},i2}, \ldots, p_{\text{best,in}})$ is determined according to the best value for the specified objective function.

Furthermore, the best position found by all particles in the population (global best position), can be represented as $g_{\text{best}} = (g_{\text{best},1}, g_{\text{best},2}, \ldots, g_{\text{best},n})$. In each step, the best particle position, global position, and the corresponding objective function values should be saved. For the next iteration, the position $x_{ik}$ and velocity $v_{ik}$ corresponding to the $k$th dimension of $i$th particle can be updated using equations as follows:

$$v_{ik}(t+1) = w.v_{ik} + c_1.rand_{1,ik}(p_{\text{best},ik}(t) - x_{ik}(t)) + c_2.rand_{2,ik}(g_{\text{best},k}(t) - x_{ik}(t)) \tag{5}$$

$$x_{ik}(t+1) = x_{ik}(t) + v_{ik}(t+1) \tag{6}$$

where $i = 1, 2, \ldots, n$ is the index of particles, $w$ is the inertia weight [22], $rand_{1,ik}$ and $rand_{2,ik}$ are random numbers in interval [0 1], $c_1$ and $c_2$ are learning factors, and $t$ represents the iterations.

Usually, a standard PSO algorithm contains the following steps.

Step 1) All particles are initialized via a random solution. In this step, each particle position and associated velocity are set by randomly generated vectors. Dimension of position should be generated within a specified interval, and the dimension of velocity vector should be also generated from a bounded domain using uniform distributions.

Step 2) Compute the objective function for the particles.

Step 3) Compare the value of the objective function for the present position of each particle with the value of objective function corresponding to prespecified best position, and replace prespecified best position by the present position, if it provides a better result.

Step 4) Compare the value of the objective function for the present best position with the value of the objective function corresponding to global best position, and replace present best position by the global best position, if it provides a better result.

Step 5) Update the position and velocity of each particle according to (5) and (6).

Step 6) Stop algorithm if the stop criterion is satisfied. Otherwise, go to step 2.

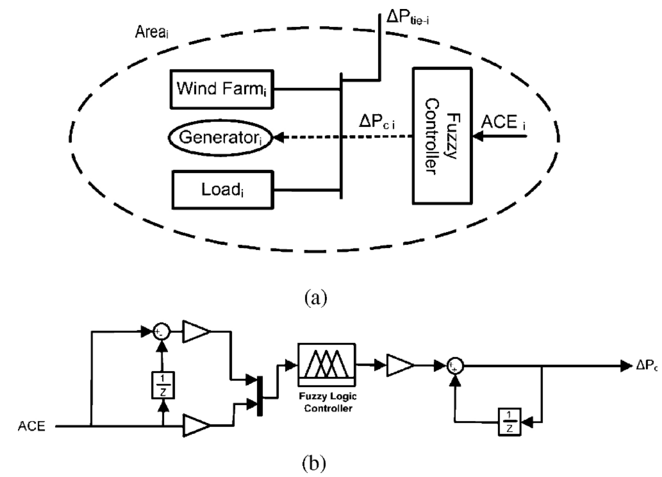


Fig. 3. Proposed control framework. (a) Area components. (b) Controller structure.

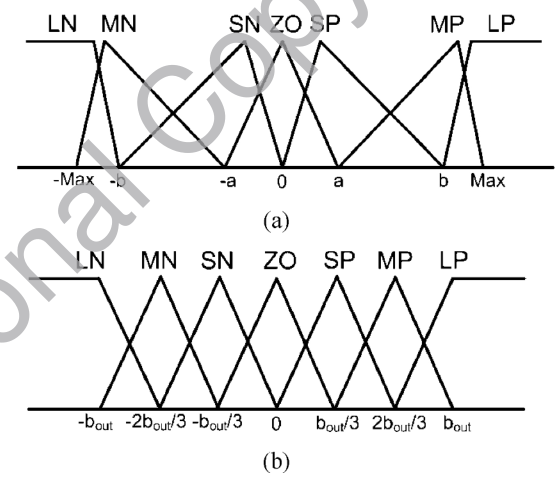


Fig. 4. Symmetric fuzzy membership functions. (a) Inputs pattern. (b) Output pattern.

In this paper, the PSO algorithm is used to find the optimal value for membership function parameters of fuzzy logic-based LFC system.

### B. Synthesis Realization

Inherent nonlinearity, increasing in size and complexity of power systems as well as emerging wind turbines and their effects on dynamic behavior of power system, caused conventional LFC systems [proportional-integral (PI) controllers] be incapable of providing good dynamical performance over a wide range of operating condition [11]. In this section, to track a desirable LFC performance in the presence of high penetration wind power in a multiarea power system, a decentralized PSO-based fuzzy logic control design is proposed. Decreasing the frequency deviations due to fast changes in output power of wind turbines, and limiting tie-lines power inter changes in an acceptable range, following disturbances, are the main goals of this effort. The overall control structure is shown in Fig. 3.

The inputs and output are brought into an acceptable range by multiplying in proper gains. In each control area, ACE and its derivative are considered as input signals, and the provided control signal is used to change the set points of LFC participant generating units. The *Mamdani*-type inference system is applied, and as shown in Fig. 4, symmetric 7-segments triangular membership functions are used for input [Fig. 4(a)] and output [Fig. 4(b)] variables. The membership functions are defined as zero (ZO), large negative (LN), medium negative (MN), small negative (SN), small positive (SP), medium positive (MP), and large positive (LP).

In this paper, in order to reach fast response from the controller system, all membership functions considered as triangular with the mathematical definition as follows:

$$\mu_X(x_i) = \max\left(0,\ 1 - \left|\frac{x - x_i}{c}\right|\right) \quad (7)$$

where $x$ and $c$ are the mean and spread of the fuzzy set $X$, respectively, and $x_i$ is a crisp variable.

Fuzzy rule base is the basis of fuzzy logic operation to map input space to the output space. Here, a rule base including 49 fuzzy rules is considered (Table I). The rule base works on vectors composed of ACE and its gradient dACE.

Using Table I, fuzzy rules can be expressed in the form of IF-THEN statements such as

**IF** ACE is SN AND dACE is MP, **THEN** output is SN.

As can be seen in the above IF-THEN statement, the antecedent part of the rules is composed of two parts, combined with fuzzy "*AND*" operators; in this paper, the combination is done based on interpreting the "*AND*" operator by *algebraic Product* operation. Considering (7), the antecedent part of above statement may be defined as follows:

$$\mu_{(\text{ACE AND dACE})}(x, y) = \mu_{\text{ACE}}(x).\mu_{\text{dACE}}(y) \quad (8)$$

where $\mu_{(\text{ACE AND dACE})}$ is the membership value of the antecedent part, and $\mu_{\text{ACE}}$ and $\mu_{\text{dACE}}$ are the membership values of ACE and dACE, respectively.

Similarly, for computing the consequent of each rule, the membership function of "Mamdani Product" implication method can be represented by

$$\mu_{\text{MP}} = \mu_{(\text{ACE AND dACE})}.\mu_{\Delta P_c} \quad (9)$$

where $\mu_{\text{MP}}$ denotes the membership function resulted by "Mamdani Product" implication, and $\mu_{(\text{ACE AND dACE})}$ is the membership value of the related antecedent part.

Since fuzzy rules are stated in terms of linguistic variables, crisp inputs should be also mapped to linguistic values using fuzzification. In order to combine rules and make a decision based on all the rules, the *sum* method is used. Finally, for converting output fuzzy set of the fuzzy system to a crisp value, the *centroid* method is used for defuzzication [23].

As the performance of a fuzzy system is influenced by the membership functions, in order to achieve good performance by the controller, a PSO algorithm is established to find the optimal value for membership functions parameters and exact tuning of them. As it can be seen in Fig. 4, each set of input membership functions can be specified by parameters $a$ and $b$, where min $< a < b <$ max. Also, for control output, one parameter is needed to be specified. Therefore, five parameters

TABLE I
FUZZY RULE BASE

| | | dACE | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | LN | MN | SN | ZO | SP | MP | LP |
| ACE | LN | LP | LP | LP | MP | MP | SP | ZO |
| | NM | LP | MP | MP | MP | SP | ZO | SN |
| | SN | LP | MP | SP | SP | ZO | SN | MN |
| | ZO | MP | MP | SP | ZO | SN | MN | MN |
| | S P | MP | SP | ZO | SN | SN | MN | LN |
| | MP | SP | ZO | SN | MN | MN | MN | LN |
| | LP | ZO | SN | MN | MN | LN | LN | LN |

TABLE II
OPTIMAL VALUES FOR MEMBERSHIP FUNCTION PARAMETERS

| $a_{\text{in,ACE}}$ | $b_{\text{in,ACE}}$ | $a_{\text{in,dACE}}$ | $b_{\text{in,dACE}}$ | $b_{\text{out}}$ |
|---|---|---|---|---|
| 0.267747 | 0.947038 | 0.013716 | 0.059880 | 0.986659 |

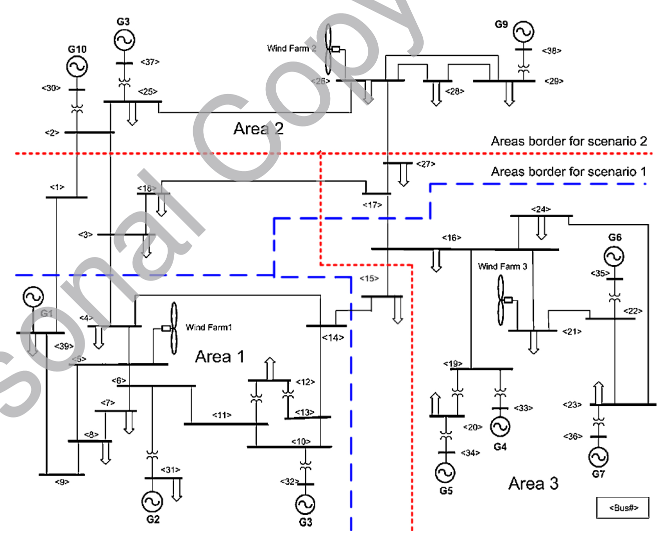


Fig. 5. Single-line diagram of 39-bus test system.

should be optimized for inputs membership functions using PSO algorithm: $a_{\text{in,ACE}}$, $b_{\text{in,ACE}}$, $a_{\text{in,dACE}}$, $b_{\text{in,dACE}}$, and $b_{\text{out}}$.

For the sake of PSO algorithm in the present LFC design, the objective function ($f$) is considered as given in (10). The number of particles, particles size, $v_{\min}$, $v_{\max}$, $c_1$, and $c_2$ are chosen as 10, 6, −0.5, 0.5, 2.8, and 1.3, respectively. Following use of PSO algorithm, the optimal values for membership function parameters are obtained as listed in Table II:

$$f = \frac{1}{3}\sum_{i=1}^{3}\left(\int t(|\Delta f_i| + |\Delta P_{tie,i}|)dt\right). \quad (10)$$

## V. TEST SYSTEM

To investigate the performance of the proposed control strategy, a network with the same topology as the well-known IEEE 10 generators 39-bus system is considered as the test system. This system is widely used as a standard system for testing of new power system analysis and control synthesis methodologies. Fig. 5 shows a single-line diagram of the test system. This system consists of 10 generators, 19 loads, 34

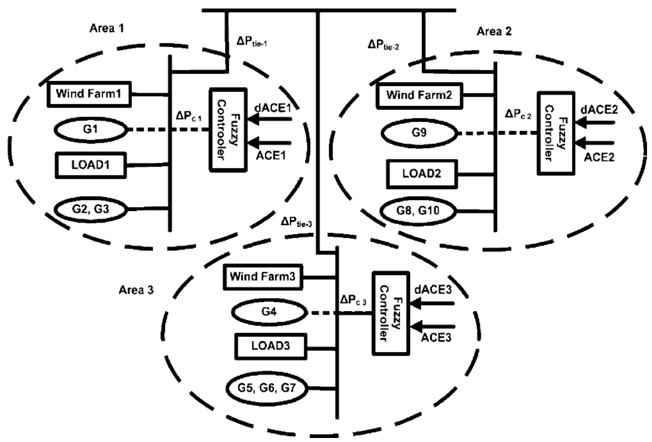


Fig. 6. Overall LFC structure.

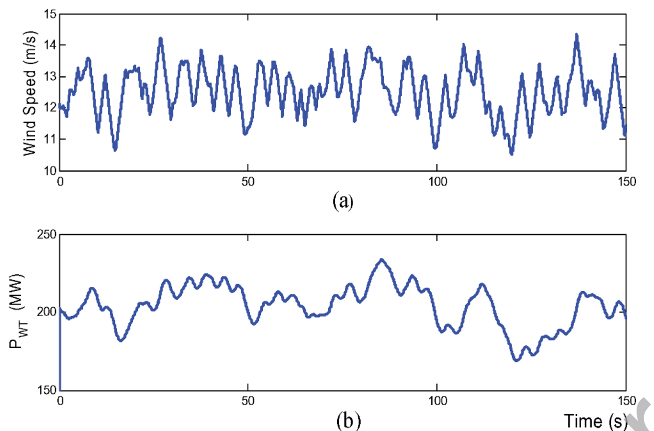


Fig. 7. Wind velocity and power in scenario 1. (a) Wind velocity pattern. (b) Total wind power generation.

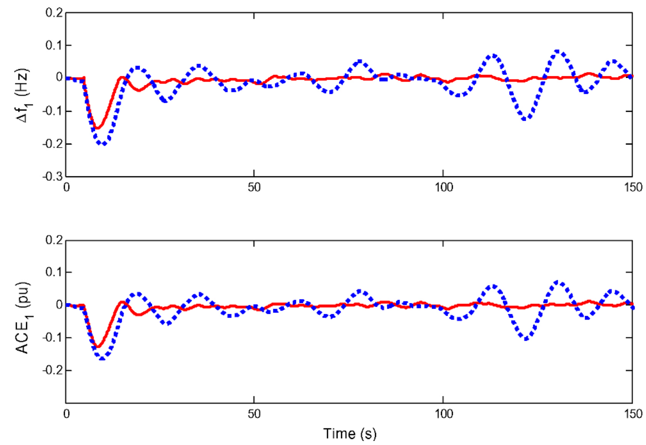


Fig. 8. Area 1 responses for scenario 1. Proposed LFC scheme (solid); conventional LFC design (dotted).

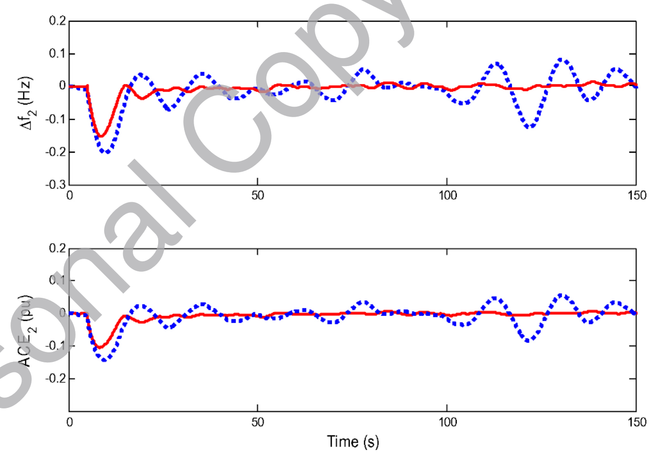


Fig. 9. Area 2 responses in scenario 1. Proposed LFC scheme (solid); conventional LFC design (dotted).



transmission lines, and 12 transformers. The power system is divided to three control areas. The simulation parameters for the generators, loads, lines, and transformers of the test system are given in [2]. As mentioned, the main objective of this paper is to propose an effective LFC scheme with a desirable performance in the presence of high penetration of wind turbines; therefore, the case study is updated by adding a wind farm to each control area. All wind farms are composed of a number of more popular type of wind turbines, i.e., DFIG. For the sake of simulation, random variations of wind velocity have been considered.

All power plants in the power system are equipped with speed governor and power system stabilizer. Fig. 6 shows a schematic block diagram which represents the decentralized fuzzy logic-based control structure for the considered power system. As it can be seen in Fig. 6, only one generator in each area is responsible for the LFC task, i.e., G1 in Area 1, G9 in Area 2, and G4 in Area 3, which are equipped with proposed fuzzy logic controller. The controllers are responsible for producing appropriate control actions ($\Delta P_c$) according to the measured ACEs and their time derivatives (dACE). To show the capability of the proposed intelligent LFC scheme, two scenarios with different rate of wind power penetrations and area deviation are considered.

## A. *Scenario* 1

For scenario 1, the start up, rated, and cut out wind velocity for the aggregated wind systems are specified as about 5 m/s, 14 m/s, and 24.5 m/s, respectively. Total system installed capacity are 582.57 MW of conventional generation and 68.4 MW of average wind power generation (10% penetration). In Fig. 5, the areas borders are shown as dashed line. There are 195.07 MW of conventional power generation, 22.7 MW of average wind power generation, and 265.25 MW load in Area 1. In Area 2, there are 157.6 MW of conventional power generation, 19 MW of average wind power generation, and 232.83 MW load.

In Area 3, there are 229.9 MW of conventional power generation, 26.7 MW of average wind power generation, and 124.78 MW load. As it is seen, the amounts of total load and generation in each area are almost equal.

## B. *Scenario* 2

For scenario 2, the total wind power penetration is increased to 30%. Furthermore, as shown in Fig. 5, the new borders (dotted line) are considered such that the difference between load and generation in each area is higher than scenario 1, and

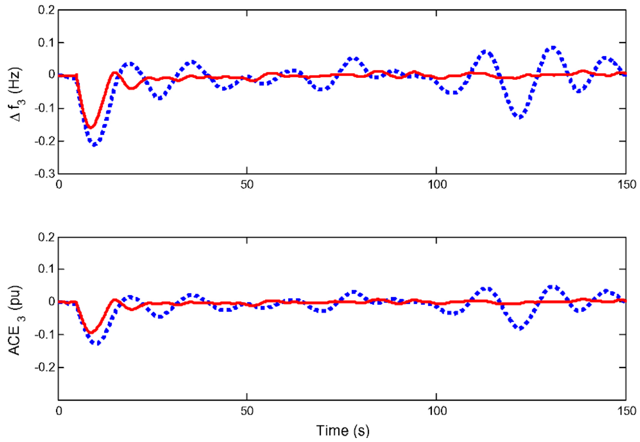


Fig. 10. Area 3 responses in scenario 1. Proposed LFC scheme (solid); conventional LFC design (dotted).

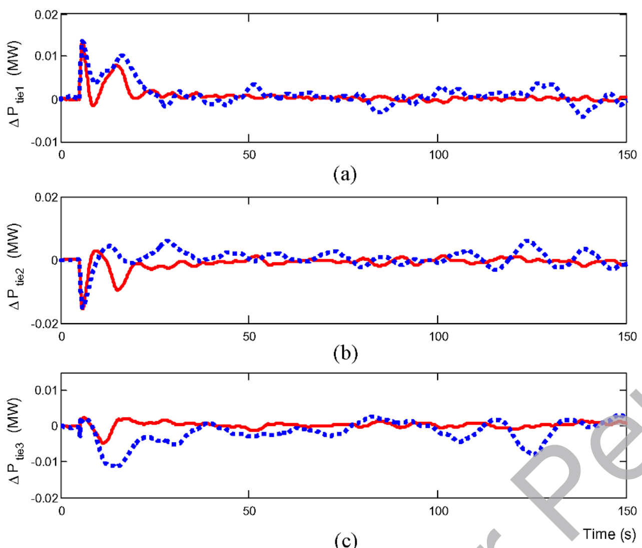


Fig. 11. Tie-line power interchanges in scenario 1. (a) Area 1. (b) Area 2. (c) Area 3. Proposed LFC scheme (solid); conventional LFC design (dotted).

three areas are pretty imbalanced in terms of generation and load.

The start up, rated, and cut out wind velocity for the aggregated wind systems are specified as about 4 m/s, 13 m/s, and 21 m/s, respectively. Total system installed capacity are 450.07 MW of conventional generation and 200.91 MW of average wind power generation. There are 152.43 MW of conventional power generation, 65.35 MW of average wind power generation, and 329.3 MW load in Area 1. In Area 2, there are 119.45 MW of conventional power generation, 57.15 MW of average wind power generation, and 74 MW load. In Area 3, there are 178.19 MW of conventional power generation, 78.41 MW of average wind power generation, and 219.6 MW load.

## VI. Simulation Results

To demonstrate the effectiveness of the proposed control design, some nonlinear simulations are performed in the SimPower environment of MATLAB software. In the simulations, the performance of the closed-loop system using the designed

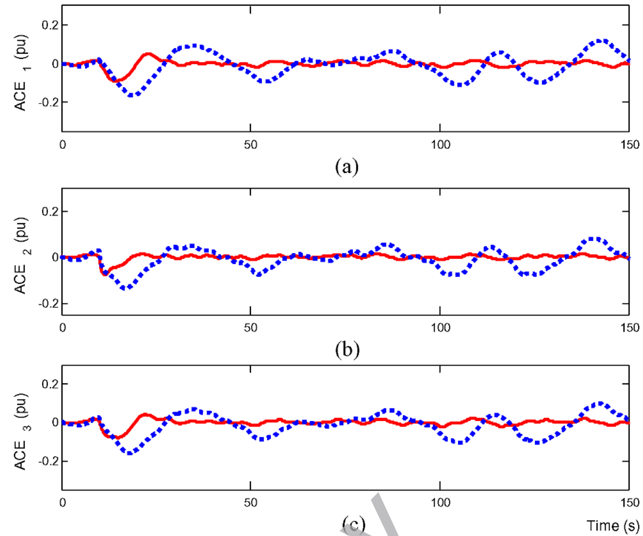


Fig. 12. ACE signals in scenario 2. (a) Area 1. (b) Area 2. (c) Area 3. Proposed LFC scheme (solid); conventional LFC design (dotted).

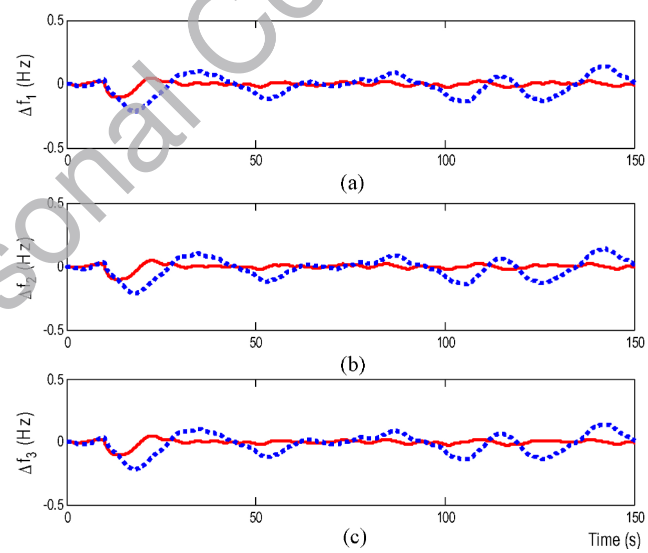


Fig. 13. Frequency deviations in scenario 2. (a) Area 1. (b) Area 2. (c) Area 3. Proposed LFC scheme (solid); conventional LFC design (dotted).

fuzzy logic-based controllers are compared with well-tuned conventional PI controllers.

As a serious test condition, three load disturbances (step increase in demand) are applied to control areas as simultaneous 6.66 pu step load increase in each area at 5 s for scenario 1 and 10 s for scenario 2. All unitized values in this paper are given based on the value of the largest generator nominal power, i.e., 150 MW.

The simulation results for scenario 1 are shown in Figs. 7–11. Wind speed pattern and total wind power generation are shown in Fig. 7. In Figs. 8–10, the ACE and the frequency deviation ($\Delta f$) of the closed-loop system for all areas are shown, following the applied load disturbances. These figures show the superior performance of proposed fuzzy logic-based LFC schemes to the conventional PI-based LFC designs in deriving ACE and frequency deviation close to zero.

Also, tie-line power interchanges of all areas are shown in Fig. 11. It can be seen that the tie-line power flows in the case of using the conventional LFC design shows more oscillations and poor performance in keeping tie-lines power interchanges in an acceptable tolerance close to the scheduled values.

System responses for scenario 2, in the face of similar load disturbances, are shown in Figs. 12 and 13. These figures show better performance for the proposed fuzzy logic-based LFC schemes in comparison of conventional PI-based LFC design in deriving ACE and frequency deviation close to zero.

## VII. Conclusion

An adaptive fuzzy logic structure was used to propose a new intelligent LFC scheme in the interconnected large-scale power systems in the presence of wind turbines. The PSO technique was applied to adjust fuzzy control parameters. The proposed method was examined on a network with same topology as the standard 10-generators 39-bus system, including wind farms. The simulation results demonstrated that the proposed intelligent LFC scheme provides desirable performance against sudden load change and wind power fluctuations in different wind power penetration rates. The achieved closed-loop performance was also compared with the application results of conventional LFC design.

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