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An on-line PSO-based fuzzy logic tuning approach: Microgrid frequency control case study

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Handbook of Research on Novel Soft Computing Intelligent Algorithms:

Theory and Practical Applications

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Chapter 20

An On–Line PSO–Based Fuzzy Logic Tuning Approach: Microgrid Frequency Control Case Study

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ABSTRACT

Modern power systems require increased intelligence and flexibility in control and optimization. This issue is becoming more significant today due to the increasing size, changing structure, emerging renewable energy sources and Microgrids, environmental constraints, and the complexity of power systems. The control units and their associated tuning methods for modern power systems surely must be intelligent (based in flexible intelligent algorithms). This chapter addresses a new intelligent approach using a combination of fuzzy logic and Particle Swarm Optimization (PSO) techniques for optimal tuning of the existing most popular Proportional-Integral (PI) or Proportional-Integral-Derivative (PID) controllers in the power electric industry. In the proposed control strategy, the PI (PID) parameters are automatically tuned using fuzzy rules, according to the on-line measurements. In order to obtain an optimal performance, the PSO technique is used to determine the membership functions' parameters. The proposed optimal tuning scheme offers many benefits for a new power system with numerous distributed generators and Renewable Energy Sources (RESs). In the developed tuning algorithm, the physical and engineering aspects have been fully considered. To demonstrate the effectiveness of the proposed control scheme, secondary frequency control problem in an islanded Microgrid (MG) system is considered a case study. The main source of power for a Microgrid is small generating units of tens of kW that are placed at the customer site. Simulation studies are performed to illustrate the capability of the proposed intelligent/optimal control approach.

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INTRODUCTION

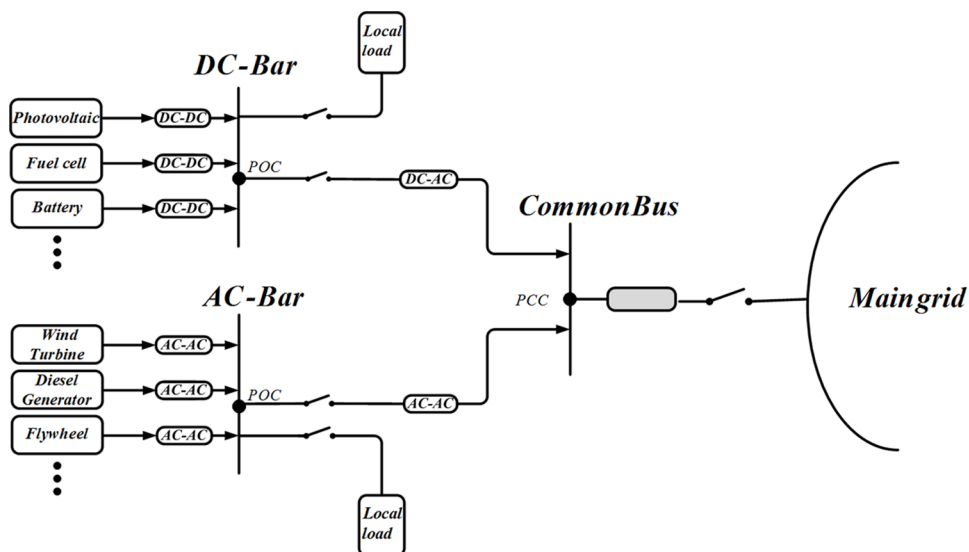
In recent years, with significant growth in electrical energy consumption, conventional generating units in power systems are faced into a variety of problems, such as global warming, energy crisis, deficiency of fossil fuels and high cost of building new power plants and so on. Hence, environmental concerns, reducing dependency on fossil fuels, improvements of new energy technologies and also enhancing the reliability of power systems, are the factors that have been affected on the entrance of Distributed Generation Resources (DGRs) such as wind turbines, solar panels, fuel cells and micro turbines to the conventional power systems in the past two decades.

The DGs are electrical power sources which are connected to the low voltage side of a bulk grid (Ackermann, Andersson, & Soder, 2001). These units generate electrical power less than ten megawatts. Although these resources have solved many problems, but increasing the numbers of them made the power systems being more complicated. Therefore, some instructions have been developed by different institutions on how to

connect these resources to the power system, like the standard IEEE Std 1547-2003 as a standard for connecting the distributed generations to the power system (IEEE, 2003). But in recent years, in order to increase the reliability of provided energy needed by consumers, there is a theory about the operation of the resources that are connected to the power grid, which is called Microgrid (Lasseter, 2002; Lasseter & Paigi, 2004). Microgrids are consisting of several distributed generations, local loads and controllers that are connected in medium/low voltage to the main grid and supplying their local loads. Junction of a Microgrid with the main grid is called Point of Common Coupling (PCC). Mostly, resources are not connected directly to the Microgrid and this work is done via the power electronic interfaces. The microsources and storage devices use power electronic circuits to connect to the MG. Usually, these interfaces depending to the type of unit are ac/ac, dc/ac, and ac/dc/ac power electronic converters/inverters. A typical Microgrid is shown in Figure 1.

New strategies will be opened by increasing number of MGs for finding a more control hierarchy/intelligence and decentralized methods

Figure 1. A typical Microgrid



particularly in the field of frequency regulation. For a MG with several DG units, droop control is one of the main control methods for keeping frequency stability similar to the conventional power systems. Control issues in the Microgrid networks are well discussed in (Bevrani, Habibi, Babahajyani, Watanabe, & Mitani, 2012). These networks must be able to provide power to their local loads properly in both connected and disconnected modes (from the main grid). When the power system subjected with a disturbance, the Microgrid transferred to islanding mode and it must be able to handle itself independently. One of the main problems facing Microgrid designers are safely/stably disconnection of the Microgrid from the main grid in a short time. Hence, control of resources, particularly in the islanded mode operation is so important, and these resources must be able to control voltage and frequency of the network.

Microgrids must also be able to manage their power (and then frequency) rapidly even the produced power is lower than the required power. In this direction, the existing storage units such as flywheels batteries have significant roles. Since in Microgrids, renewable energies such as solar and wind energy, are mostly used with considering the unpredictable nature of these sources, and also with considering the probability nature of disturbances occurred in power systems, controlling the basic parameters of the grid such as frequency and voltage are so important.

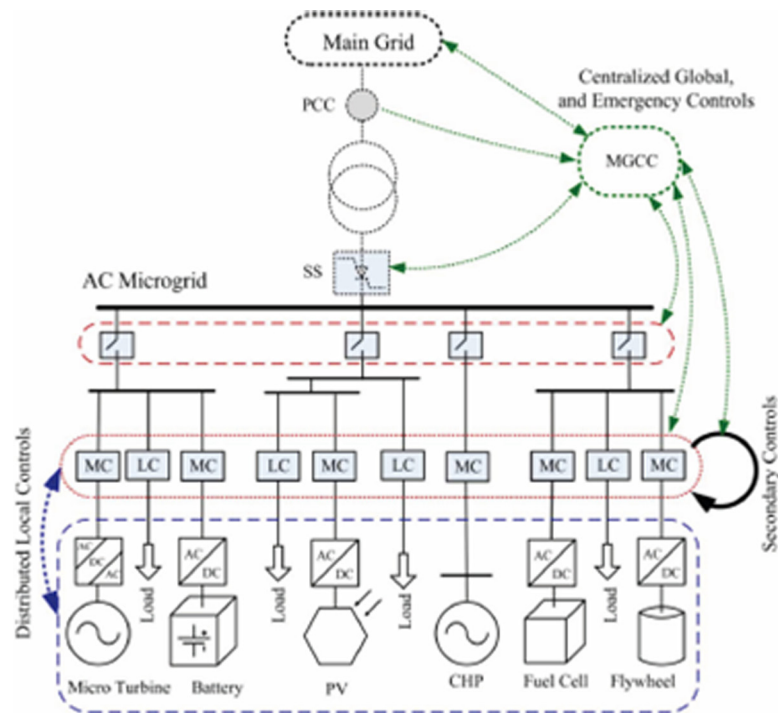
To achieve these control objectives, in islanded mode operation there are several types of control approaches which can be categorized as central, single-agent, and decentralized controls. In the central control approaches, MG has a central control unit that collects data from all DGs and decides for Microgrid state based on the collected information. In load variation states, central control unit shares extra load among all DGs based on the information of producers. More details about this approach are presented in (Gil & Lopes, 2007; Lopes, Moreira, & Madureira,

2006; Madureia, Moreira, & Lopes, 2005; Yuen, Oudalov, & Timbus, 2011).

In the single-stage control approaches, MG has a great controllable DG for the sake of frequency control issue and establishes balance between production and consumption among the MG. An example is given in (Marinescu & Serban, 2009). Although in this method non controllable generations can be also used, but the main problem of this approach is the high cost of the controllable DGs and dependency of the Microgrid stability to these sources. In decentralized control attitude, each DG is controlled through a local controller. So none of these generations is reference, and all of them have the same degree of controllability; then if one of them is collapsed, the others have not been affected. In another word each DG or local load is equipped with a local controller. Some examples are given in (Barklund, Pogaku, Prodanovic, Hernandez-Aramburo, & Green, 2008; Datta, Senju, Yona, Funabashi, & Kim, 2009; Diaz, Gonzalez-Moran, Gomez-Aleixandre, & Diez, 2010; Ina, Yanagawa, Kato, & Suzuoki, 2005; R.H. Lasseter et al., 2011; Pogaku, Prodanovic, & Green, 2007). A general scheme for different control strategies in a MG is shown in Figure 2.

In the conventional power systems, in order to stabilize the frequency, two main control loops are usually available, which are known as primary and secondary control loops. Following a disturbance, an imbalance may happen between generation and consumption. The primary control loop preserves the frequency against the permanent droop and the secondary control loop returns the frequency to the nominal value. Often in secondary loop, conventional PI controller is used. Since in controller design based on the classical methods, the systems are considered at their nominal operating points, the synthesized controllers are not able to provide an optimum performance in the presence of uncertainties including disturbances, system parameters and load changing. Thus, due to inefficiency of the

Figure 2. A general scheme for microgrid controls (H. Bevrani et al., 2012)



classical methods in frequency stabilizing, applying an effective methodology to update the controller parameters and to compensate the impacts of the changes happened in the system, is obligatory. Using intelligent systems, such as a fuzzy system for on-line regulating of controller parameters, can be considered as a proper solution. This control strategy recognized as adaptive control.

In this chapter, a fuzzy system is used to handle the control parameters tuning action, and as it will be discussed later, Particle Swarm Optimization (PSO) is used to cover the challenge of dependency of the fuzzy systems to their membership functions (Bevrani & Hiyama, 2011).

This chapter is organized as follows: a background and literature review on the MG, frequency control, fuzzy logic and PSO are given in the *background* section. In the next section, the MG test system is introduced. The proposed design is enhanced by the PSO algorithm for

adjusting the fuzzy member functions parameters in the *proposed optimal control design* section. At the end, *simulation results, discussion, future research directions* and *conclusion* parts are provided.

BACKGROUND AND LITERATURE REVIEW

Fuzzy Logic

The concept of fuzzy logic was first proposed in 1965 by Professor Zadeh, in order to response to the inability of the classic control theory to covering the complex systems with uncertainties and inaccuracies (Zadeh, 1965). A fuzzy system, is a nonlinear system were based on human knowledge, and capable to convert this knowledge, were expressed in the form of verbal phrases, to the mathematical rules and mapping

nonlinear relationships between the input and output space.

A fuzzy system is composed of four main sections (Mendel & Mouzouris, 1997): fuzzification, fuzzy rule base, inference system and defuzzification. Fuzzification is converting the numerical values into the spoken expressions. In a fuzzy system, variables are expressed in terms of spoken phrases, so before the numerical inputs can be applied to the fuzzy system, they should be converted to speech values. This is done in the fuzzification step. Generally, phrasal variables are denoted by the number of functions or lookup tables, called membership function or fuzzy set. Considering these functions, or lookup tables, it can be said that fuzzification is estimating of an amount, usually between zero and one, which shows degrees of dependency to each entry in fuzzy set. Each fuzzy system works based on a set of conditional sentences with IF-THEN structure that has the verbal concepts (Mendel & Mouzouris, 1997), and introduced as Fuzzy rules. These rules are generally expressed as follows:

$$\begin{array}{l} \text{IF } x_1 \text{ is } A_1, \text{ and } x_2 \text{ is } A_2, \text{ and } \dots, \\ \text{THEN } y \text{ is } B \text{ for } i=1, 2, \dots, n \end{array} \quad (1)$$

where x_i and y are the input and output variables respectively, and A_i and B are the verbal fuzzy sets. The IF part of each fuzzy rule is called *antecedent* and the THEN part is called *consequent*. Generally, these rules are extracted using the knowledge and experience of professionals who are working in the studied field. In fact, the inference system can be considered as the engine of the fuzzy system. Its duty is interpreting and compositing the rules and imaging the inputs to the outputs through the sets of fuzzy rules. Generally the fuzzification interface can be pointing in accordance with the following steps (C.C. Lee, 1990a):

1. Measuring the values of input variables.
2. Performing a scale mapping that transfers the range of values of input variables into corresponding universes of discourse.
3. Performing the function of fuzzification that converts input data into suitable linguistic values which may be viewed as labels of fuzzy sets.

In the defuzzification step, the inference system output, that is a fuzzy set, is converted to a numeric value. A fuzzy inference system output is usually a fuzzy set that results from the consequent of the rules. This fuzzy set must be converted to a numeric value to be used as the output of the fuzzy system. This is usually done by a function in the defuzzification step. In fact, designing a fuzzy system is reduced to determine the parameters and functions related to these four parts. So, according to the above explanations, it can be concluded that in order to design of intelligent controllers for dynamical systems one can use the applications of fuzzy logic. For designing a fuzzy controller, the key point is to determine functions and parameters that are used in the fuzzy system.

As mentioned before, fuzzification is based on mapping the numerical amounts to fuzzy sets with oral values. Generally, the fuzzy sets are interpreted with membership functions (μ_x), that are corresponding to amounts between zero and one, for each numerical value (x). The membership functions are usually determined by the designer and in fact, it is optional. Different forms are introduced for these membership functions such as trapezoidal, triangular and Gaussian functions (Lee, 1990a; Mendel & Mouzouris, 1997). The most common form of membership function in fuzzy control design is the triangle function. Actually, fuzzy rules constitute the dynamic behavior of the fuzzy controllers (Lee, 1990a), hence play an important role in fuzzy system. The number of rules in a fuzzy set is

determined by the number of inputs and outputs and the number of membership functions.

As it mentioned before, the IF part of any fuzzy rule is called antecedent. This section is comprised of numerous fuzzy sentences that are combined with one or more fuzzy operators like AND, OR and NOT. These operators combine the membership quantities, obtained for each input in fuzzification step, and corresponding the antecedent part to a numerical value that is used to calculate the result of each fuzzy rule. Several functions have been introduced to describe these operators in (Lee, 1990b). The fuzzy rules are used by the inference unit, which is a function for applying to the numerical value obtained from the antecedent part and providing the results of each fuzzy rule as a transformed membership function of the output membership functions. One of the most common inference rules which is widely used in the fuzzy systems, is *mamdani's fuzzy inference*.

In order to calculate the fuzzy output set, the obtained fuzzy set of all fuzzy rules should be combined, that there are several ways to combining these rules. Since the fuzzy controller output is must be a numeric value, the obtained fuzzy set from the combination of fuzzy rules should be converted to a numeric value. Some common methods of defuzzification including maximum criteria, minimum of maximum, center of gravity and center average are reported in (Lee, 1990b).

According to above descriptions, since the performance of a fuzzy system is substantially depends on its membership functions, in order to achieve a good performance, for finding optimal quantities for the parameters of membership functions and fine-tuning of them, effective optimization algorithms is necessary to adjust their parameters. Among the available useful algorithms in this context, the PSO can be pointed.

Particle Swarm Optimization (PSO)

The PSO algorithm is an optimization technique based on the probability laws, which inspired from the natural models. This algorithm is classified as direct search methods and is used to find the best response of the optimization problems in a given search space.

This algorithm was presented by Russell Eberhart and James Kennedy in 1995, with ideas of social behavior of birds in finding food (R. Eberhart & Kennedy, 1995; Kennedy & Eberhart, 1995a). In this algorithm the search process can be introduced in this way that, a group of birds is randomly looking for food in a particular region. There is only one area of the region that has food and the birds are not aware of that area, but they know their distance at each step of the searching process. So, to get closer to the location of the food, all of the birds are following the bird that has the nearest distance to the food place. In this algorithm, each bird is introduced as a particle and all of the particles form a group or swarm. Each particle is determined with two vectors $X(t)$ and $V(t)$ that respectively represent the location and velocity of the particle at the time (t) , and position of each particle is potentially considered as a solution for the problem. Then, to find the best position (the best solution) at each time, the particles are flying around the search area and change their speed and position. All of the particles regulate their route based on their experience and the others of the last moment of flight (Tang & Zhao, 2009). In an n -dimensional search area, position and velocity of i^{th} particle at time t are respectively shown with the following vectors:

$$\begin{aligned} V_i(t) &= [V_{i1}(t), V_{i2}(t), \dots, V_{in}(t)]^T, X_i(t) \\ &= [X_{i1}(t), X_{i2}(t), \dots, X_{in}(t)]^T \end{aligned} \quad (2)$$

At each time, particles are corresponded with an objective value and the best positions of the particles from the beginning to this moment have been stored by the algorithm. The best position for a particle, at time t , is a position which based on that the particle has the best objective value. The best position for the i^{th} particle up to the time t , is represented as:

$$p_{\text{best}i}(t) = [p_{\text{best},i1}(t), p_{\text{best},i2}(t), \dots, p_{\text{best},in}(t)] \quad (3)$$

The PSO also stores the best position that is obtained by all of particles up to the time t , which it can be shown as below:

$$g_{\text{best}}(t) = [g_{\text{best},1}(t), g_{\text{best},2}(t), \dots, g_{\text{best},n}(t)] \quad (4)$$

where, X_{ij} and V_{ij} are j^{th} element of the velocity vector V and position vector X for the i^{th} particle, respectively (Tang & Zhao, 2009). Each particle position and velocity pair at time $(t+1)$ is obtained as follows:

$$\begin{aligned} v_{ij}(t+1) = & w.v_{ij}(t) + c_1.\text{rand}1_{ij} \\ & .(p_{\text{best},ij}(t) - x_{ij}(t)) + c_2.\text{rand}2_{ij} \\ & .(g_{\text{best},j}(t) - x_{ij}(t)) \end{aligned} \quad (5)$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \quad (6)$$

where $i=1, 2, \dots, n$ is particle index, x_{ij} is the j^{th} dimension of the i^{th} particle position, v_{ij} is the j^{th} dimension of the i^{th} particle velocity, $p_{\text{best},ij}$ is the j^{th} dimension of the best position of the i^{th} particle at time t , $g_{\text{best},j}$ is the j^{th} dimension of the best position that so far achieved by all of the particles, W is the inertia weight. The $\text{rand}1_{ij}$ and $\text{rand}2_{ij}$ are two random numbers in the interval $[0, 1]$; c_1 and c_2 are training factors and t is the time or iteration. The effect of parameters and their recommended values are discussed in (Eberhart, 1998).

Up to now, many search algorithms have been proposed in order to solve the optimization problems such as genetic algorithm, ant colony, and bee colony. However, simplicity is the main advantage of PSO algorithm in comparison with other methods, especially genetic algorithm. Several solutions have been proposed to improve the performance of the PSO algorithm (Dong, Wang, & Chen, 2008; Meijie, Hanxing, Weiwe, & TongLin, 2007; Tang & Zhao, 2009).

In the present chapter, main objective is designing an adaptive controller using fuzzy logic and PSO algorithm in order to control the frequency of a Microgrid in islanding mode. There are several approaches toward the membership function adjustment such as trial and error, and online regulating membership function method using a complementary optimization algorithm. Up to now, many search algorithms have been proposed in order to solve the optimization problems, including Genetic Algorithm (GA), ant colony, and bee colony. Considering the LFC features and the previous experience on various intelligent approaches, in the present work the PSO is used as a flexible and powerful intelligent algorithm for online tuning of membership functions employed in the fuzzy PI controller. The PSO is an optimization algorithm, based on the probability laws, which is inspired by the natural models. This algorithm belongs to class of direct search methods and is used to find an optimal solution for the optimization problems in a given search space. Basic difference of the PSO algorithm in comparison with other intelligent methods is in the simplicity of implementation. Other outstanding features of the PSO algorithm can be pointed as follows (Kennedy & Eberhart, 1995b):

- It uses the cost function information to navigate search action in the problem space.
- Only numerical values for the cost functions can be used. This feature facilitates

the PSO to use on the non-derivative cost functions.

- In comparison of other methods, due to use of probability rules, more flexible and robust control frameworks can be achieved by the PSO algorithm.
- The PSO provides a high accuracy result, without using complex operations.
- It is able to overcome premature convergence which increases the search action ability.
- Achieving to the optimal response from any given initial search point is guaranteed.
- The calculation time in comparison of other optimization methods such as GA is much less.
- It is easy to use the PSO in online and real-time optimization states.

LITERATURE REVIEW

An introduction of the DG units and their mathematical models, such as wind turbines, PV panels, diesel generators and energy storage devices including batteries and flywheels are presented in (Basak, Saha, Chowdhury, & Chowdhury, 2009; Chowdhury, Chowdhury, & Crossley, 2009).

The MG and its infrastructure reasons are addressed in (Chowdhury et al., 2009; Lasseter, 2002; Lasseter et al., 2002; Lasseter et al., 2011; Lasseter & Paigi, 2004). As mentioned in the Consortium for Electric Reliability Technology Solutions (CERTS), the MG concept assumes an aggregation of the loads and MicroSources (MSs) operating as a single system providing both power and heat. The advantages and challenges which are caused by entrancing of the MGs into the main grid have been studied in (Chowdhury et al., 2009; Lasseter, 2002; Lasseter et al., 2002; Lasseter et al., 2011; Lasseter & Paigi, 2004; Zaidi & Kupzog, 2008). Control issues and methods such as PQ, VSI, Single Master Operation (SMO),

and Multi Master Operation (MMO) methods are presented in (Lasseter et al., 2002; Lasseter et al., 2011; Lasseter & Paigi, 2004).

In the SMO and MMO, the voltage and frequency references are respectively generated by one Voltage Source Inverter (VSI) and multi VSIs. In connected mode, the PQ method is used to inject constant real and reactive powers from DGs to main grid. In the VSI mode, the MG and main grid are in the disconnected mode and the MG generates voltage and frequency references by itself.

Frequency control synthesis and analysis in power systems has a long history and its literature is voluminous. System frequency is deviated from its nominal value if an unbalancing occurs in the consumption and generation. Two major control loops of primary and secondary (supplementary) are mostly used for keeping the system frequency stability. The primary control loop is equipped on the synchronous generator and acts based on the droop characteristic. This control phase prevents instability of the system frequency due to unbalancing, but it is unable to return the system frequency to the nominal value. Steady state error in the system frequency profile is compensated by a secondary (supplementary) control loop. In the secondary control loop is mainly used from the classical PI/PID controllers. In (Bevrani, 2009) about the system frequency and different control methods, some information have been comprehensively presented. In the context of intelligent system frequency control several works have been so far reported as (H. Bevrani, Habibi, & Shokoochi, 2013). In this study, to find an optimal performance for the PI controller, Artificial Neural Networks (ANNs) were used as a supervisor unit to online tuning of the controller parameters.

Most of conventional LFC synthesis methodologies provide model based controllers that are difficult to use for 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 (Bevrani, 2009).

The LFC systems and their associated tuning methods for modern power systems, which should handle complex multi-objective regulation optimization problems characterized by a high degree of diversification in policies, control strategies and wide distribution in demand and supply sources, surely must be *intelligent*. The core of such intelligent system should be based on flexible intelligent algorithms (Bevrani & Hiyama, 2011; Gautam, 2010; Mazinan, 2010; Rakhshani, 2012; Sheikh et al., 2012; Subbaraj & Manickavasagam, 2008; Toppo, 2012).

During last few years, several reports presenting various control methods on the frequency regulation, real power compensation, and tie-line control issues, have been published. Some recent works address intelligent control techniques for the frequency regulation/LFC issue in the power systems. Several studies have been already reported for the fuzzy logic-based LFC design schemes in the literature (Bevrani & Daneshmand; Rao, Nagaraju, & Raju, 2009), 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.

A combined LFC design method for a two-area power system based on the PSO algorithm and optimal output feedback control is given in (Rao et al., 2009). In (Subbaraj & Manickavasagam, 2008) and (Gautam, 2010), a self-tuning fuzzy controller with Superconducting Magnetic Energy Storage (SMES) unit is used to perform the LFC system in a two area power system. A PID-based LFC scheme using the PSO algorithm is considered in (Rakhshani, 2012) for a single area hydropower system. (Sheikh et al., 2012) presents the application of an improved PSO

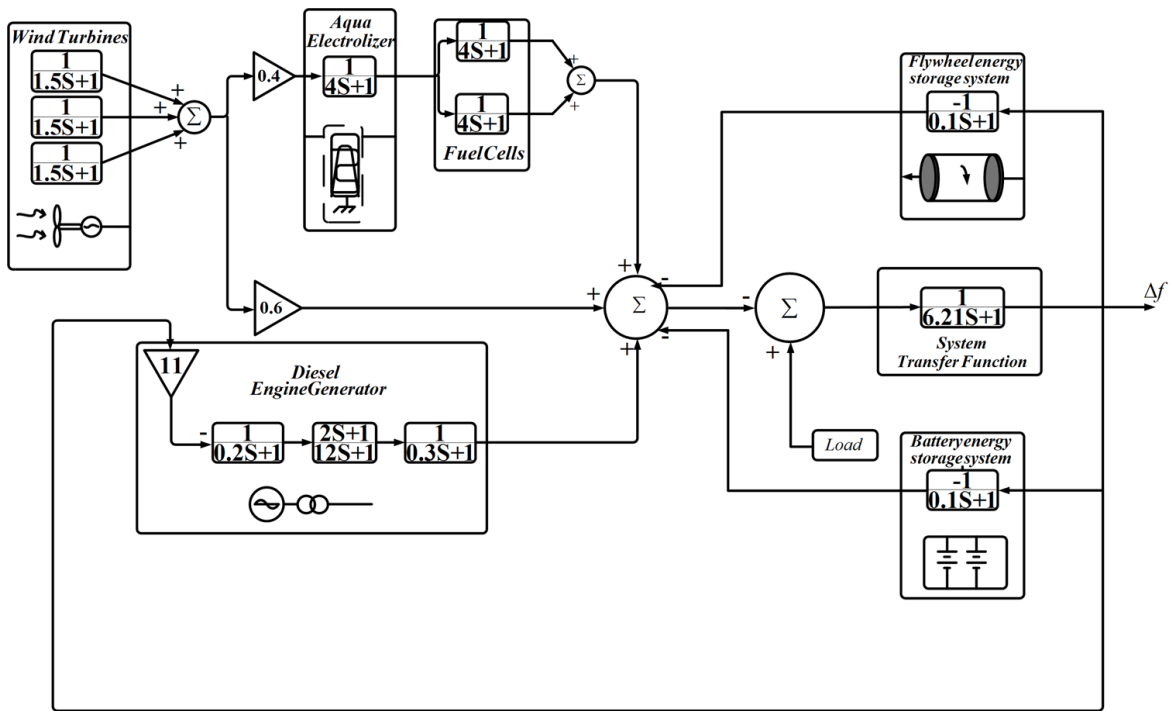
algorithm for a PID-based LFC in a single area power system. A combination of fuzzy logic and linear generalized predictive control is also applied for the LFC synthesis in a two-area power system in (Toppo, 2012.). Finally, (Mazinan, 2010) suggests a PSO based multi-stage fuzzy controller for the LFC system under a bilateral policy scheme.

MICROGRID TEST SYSTEM

The considered Microgrid model where used to examine the proposed optimal control methodology, is shown in Figure 3. This model consists of three Wind Turbines (WT), two Fuel Cells (FC) and one Diesel Engine Generator (DEG). Required hydrogen for the fuel cells supplied through an Aqua Electrolyzer (AE) unit. The AE is used to convert a part of the generated power from wind turbines into available hydrogen to offer the required fuel for fuel cells. It also has an energy storage system including a Battery Energy Storage System (BESS) and a flywheel energy storage system (FESS), which both are installed at the load side. When the Microgrid cannot responsive to the load production rate, these sources inject an appropriate amount of energy into the grid in a very short time. More details on the MG test system and its parameters can be found in (Lee & Wang, 2008).

A simplified frequency response model of the studied Microgrid is shown in Figure 3. The changes pattern of the output power of the WTGs and FCs and frequency response of different micro source units to a step load change (ΔP_L) at the 50th second of the simulation process are shown in Figure 4. As it can be seen, the Microgrid is not able to fully compensate the frequency drop due to the step load disturbance. Hence, a proper controller is needed to recover the system frequency and to remove the occurred steady state frequency error.

Figure 3. Frequency response model of the Microgrid case study



PROPOSED OPTIMAL CONTROL DESIGN

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 optimization and 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.

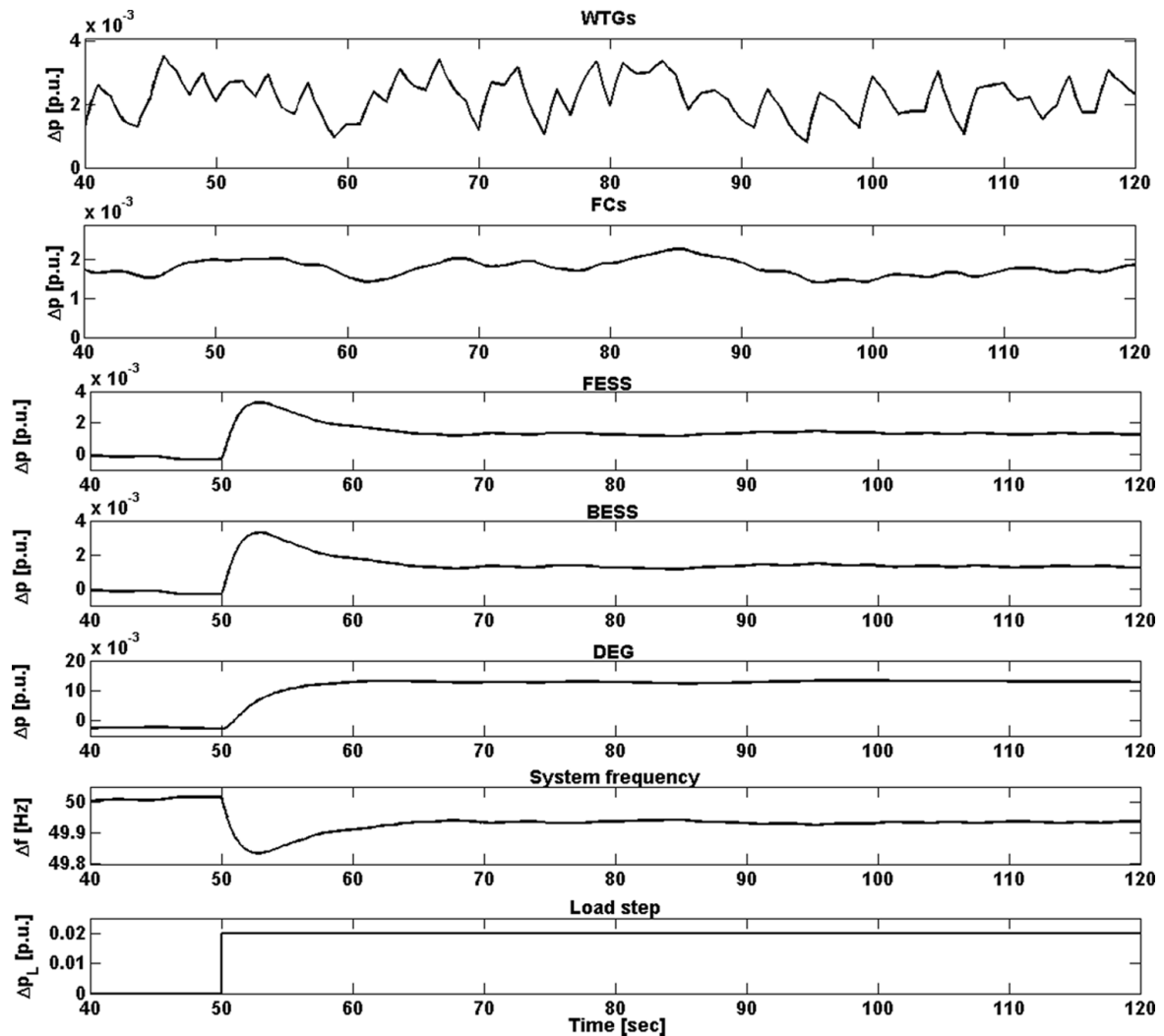
The applications of fuzzy logic in control systems can be classified into two main categories: *i)* using fuzzy logic system as a dynamic controller, *ii)* using fuzzy logic alone or together with another intelligent/searching algorithm as a primer for tuning the gains of the existing PI

(or PID) controller. Here, in order to control of Microgrid system frequency, second category has been used.

Fuzzy PI control

The PI and PID control structures have been widely used in power system control due to their design/structure simplicity and inexpensive cost. Among these controllers, the most commonly used one in AGC systems is PI controller (Bevrani, 2009; Bevrani & Hiyama 2011). Optimal performance of these controllers depends on proper tuning of their coefficients, which often is practically done by using professionals' experiences, try and error and using classical methods. As mentioned before, by using these classical methods, systems are considered in their nominal operating points and thus the obtained controllers cannot be able to adapt themselves with probable changes and disturbances happened

Figure 4. Frequency response of different Microgrid units to a step load disturbance



to the systems. So using a monitoring system for online tuning of main control parameters (mostly PI), in real time and accordance with system conditions is highly needed.

In this section, in order to achieve such a goal, a design methodology for an adaptive PI controller is addressed. This controller has two levels: first a conventional PI controller which is the main controller and second, a fuzzy system to regulate the PI controller parameters (and) in real time. As previously mentioned, the fuzzy PI controller has two levels which the first one is

a conventional PI controller and the second one is a fuzzy system. Frequency fluctuation signal and the amount of load change perform the fuzzy system input variables. With respect to these inputs, the fuzzy system produces appropriate coefficients of the PI controller as the output variables (signals). In order to express the control variables in the form of objective values, each fuzzy input and output signals are corresponded with a set of membership functions consisting several triangular functions (Bevrani & Hiyama, 2011). Membership functions corresponding

Table 1. The set of fuzzy rules

Δf ΔP_i	NL	NM	NS	PS	PM	PL
S	NL	NM	NS	PS	PS	PM
M	Nl	NL	NM	PS	PM	PM
L	Nl	NL	Nl	PM	PM	PM

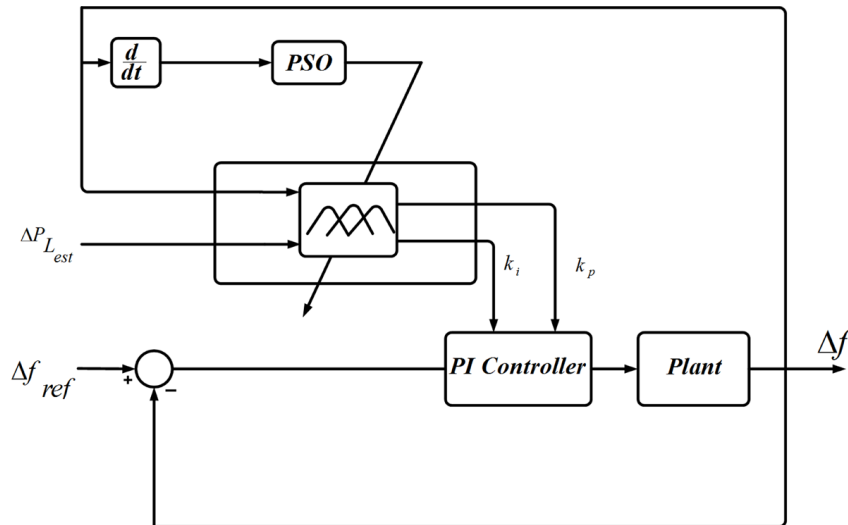
to the input and output variables are named as Negative Large (NL), Negative Medium (NM), Negative Small (NS), Positive Small (PS), Positive Medium (PM) and Positive Large (PL). A set of fuzzy rules including 18 rules (See Table 1) is used to map the input variables to the output variables. The antecedent part of each rule is composed using the AND function (with interpretation of *minimum*). Here, the Mamdani fuzzy inference system is also used. For an example, one of these rules is extracted as follows:

If Δf is NS and ΔP_i is M then Output (K_i or K_p) is NM.

Optimal Fuzzy PI Control

As mentioned, in this study, the PSO algorithm is used to achieve an optimal performance for the fuzzy system. The optimal performance of a fuzzy system is highly related to the parameters of membership functions. Here, the PSO is used to tune the membership functions. Implementation of the proposed method and the results of simulations in MATLAB/SIMULINK environment show a desirable performance and efficiency of the proposed control strategy. The block diagram of the proposed optimal tuning strategy is shown in Figure 5.

Figure 5. The closed-loop system with optimial fuzzyPI controller



The performance of this algorithm heavily relies on some terms, such as cost function, conditions for stopping the algorithm and the initial values of algorithm parameters. The purpose of this algorithm is finding the extremum point of the cost function; if the cost function is not properly selected, the extremum point of the cost function cannot be considered as an optimal solution for the problem at hand. If the stopping conditions are not also properly determined, the algorithm may stop before finding the global extremum point, or because of too much investigating of the search space, the algorithm response would be so slow, or due to not satisfying the stop conditions, even if the extremum point is found, the algorithm could not be able to recognize it as the correct response. Initialization of the algorithm parameters is so important, because if they are not correctly selected, the PSO algorithm may never converge to the extremum point. What is defined as the cost function to achieve these ends (stop points) is the derivative of the frequency changes of the Microgrid ($d\Delta f$), because if it being zero the frequency deviation will approach to zero and the algorithm will stop, automatically because the stopping criterion is satisfied.

To discover the parameters tuning details look at (Khare & Rangnekar, 2012). Generally, for each case, the proper values of the PSO algorithm parameters have been achieved by trial and error during several simulation scenarios.

The important parameters of the PSO algorithm are the number of the particles, particles dimension, particles velocity interval (V_{max} , V_{min}), c_1 , c_2 and particles place interval (X_{max} , X_{min}).

In general, the PSO algorithm is used in accordance with the following steps:

1. Selecting the algorithm parameters including V_{min} , V_{max} , N (number of the particles), c_1 , c_2 , X_{min} , X_{max} and W (inertia

weight) that is assumed to be 0.9 in this study.

2. Initializing particles ($X_i(t)$, $V_i(t)$), randomly.
3. Initializing the P_{best} vectors for all of the particles using the random initial values obtained in step 2 for the position vectors.
4. Updating the fuzzy system parameters using particle position vector ($X_i(t)$) and calculate the fitness value for each particle using the specified cost function.
5. Determining the g_{best} using the objective values of the particles.
6. Updating the inertia weight using the weight function given as follows; where F is the objective value of each particle (Tang & Zhao, 2009).

$$W = [3 - e^{\frac{-n}{200}} + (\frac{F}{100})^2]^{-1} \quad (1)$$

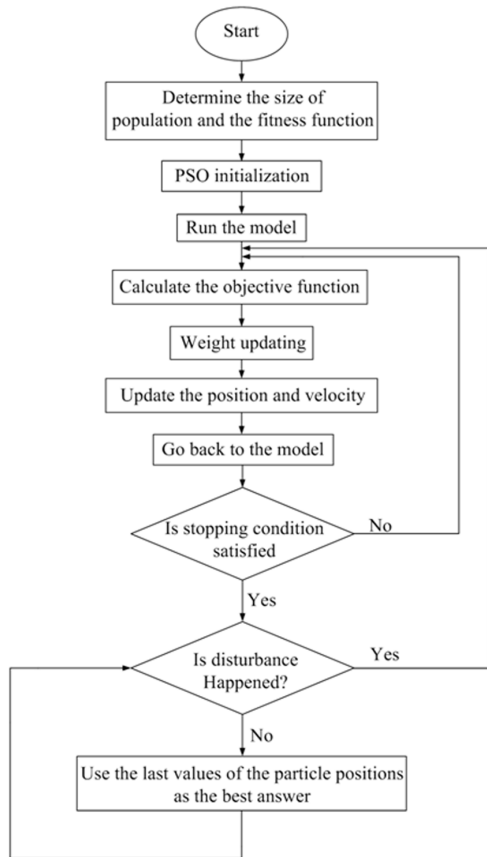
7. Updating the particles velocity vectors V_i and position vectors X_i according to (5) and (6),
8. Updating the parameters of the fuzzy system membership functions by the position vector of each particle and calculating the objective value for each particle,
9. Updating the P_{best} for each particle,
10. Updating the g_{best} ; if the objective value of the $g_{best}(t+1)$ is better than the objective value of the $g_{best}(t)$, then

$$g_{best} = g_{best}(t+1) \quad (2)$$

11. If the stopping condition is met, algorithm is stopped and the optimal parameter values are achieved, otherwise return to step 6.

The PSO algorithm can be summarized as shown in the flowchart of Figure 6, and also, the

Figure 6. Online PSO algorithm



overall method is graphically shown in Figure 13 at the Appendix.

SIMULATION RESULTS

In this section, in order to study the performance of the proposed optimal fuzzy PI controller, some simulations have been done in MATLAB/SIMULINK environment for the introduced Microgrid test system (Figure 3). The performance of the conventional PI, fuzzy PI, and optimal fuzzy PI controllers are also compared in the presence of load change disturbance.

Simulation results depict that the fuzzy PI controller performs a better rise time and settling time than the classical PI controller. Moreover, covering the system uncertainties can be considered as main advantage of the fuzzy PI controller due to the adaptive property of the applied fuzzy logic, where the classical controllers will not handle it.

However, the fuzzy PI controller provides a quite better performance, if the fuzzy system

Figure 7. The results of applying the classical PI, fuzzy PI and optimal fuzzy PI controllers

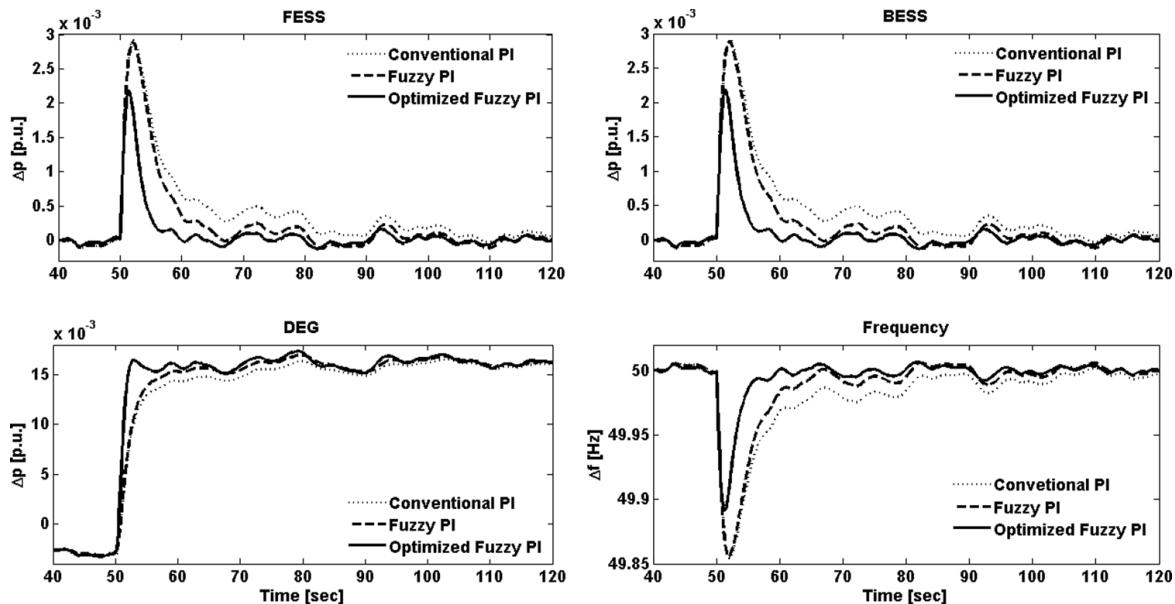


Figure 8. The results of applying the classical PI, fuzzy PI and optimal fuzzy PI controllers in the presence of wind turbines outage

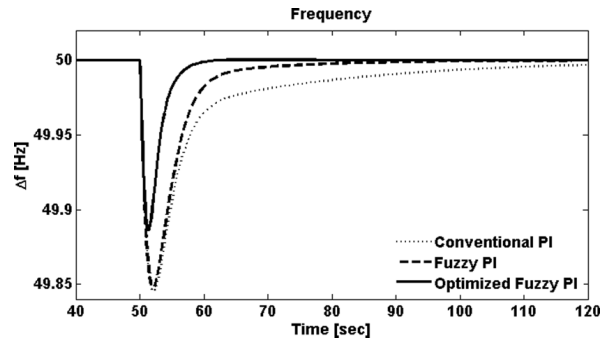


Figure 9. Particles movement

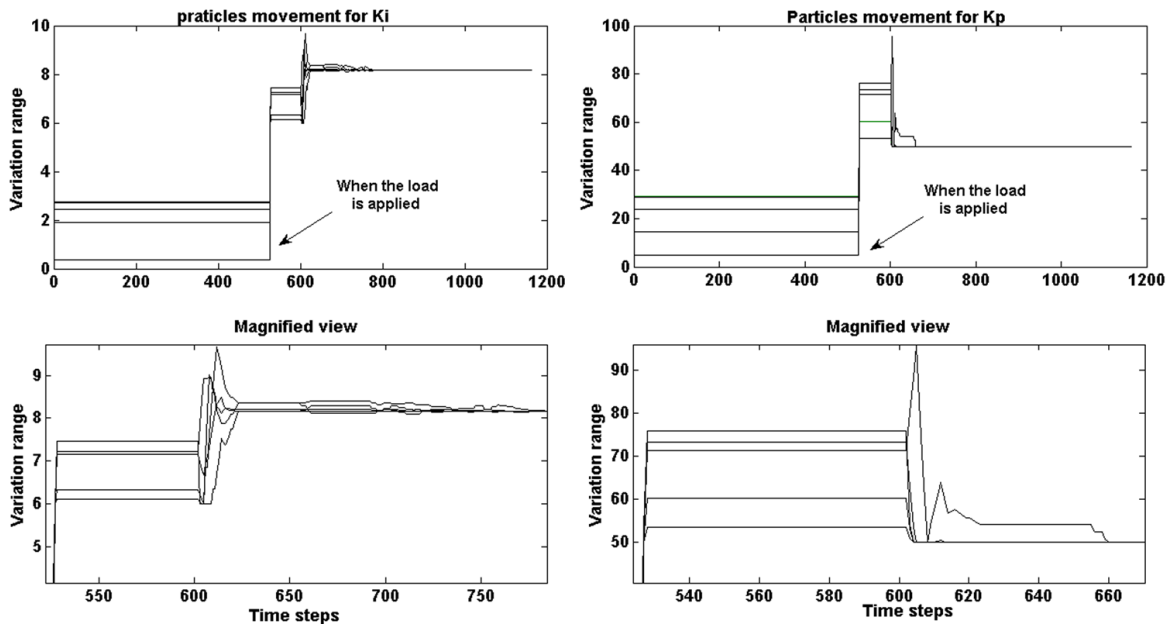
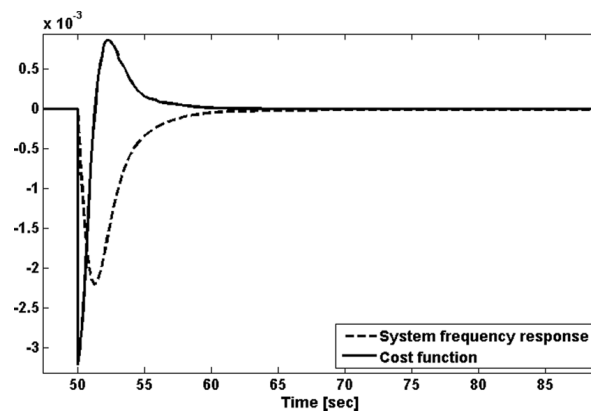


Figure 10. System frequency response and cost function



membership functions are optimized. Because as mentioned before, fuzzy system performance is highly dependent on the employed membership functions. As mentioned, in order to remove the try and error element in setting of membership function parameters, the PSO algorithm is used to optimize these function parameters. The results of applying the classical PI, fuzzy PI and optimal fuzzy PI controllers are compared in Figure 7, which the effectiveness of using the PSO in parameters tuning can be clearly seen.

To investigate the performance of the controllers and their differences, clearly; previous experiment is repeated, under condition of wind turbines outage. The results are shown in Figure 8. As mentioned before, 10 particles have been used for training the fuzzy system, which their paths to the answers, during the simulation time, (extremum point) are shown in Figure 9. Cost function has been also shown in Figure 10.

Figure 11. Frequency response under the condition of 20% changes

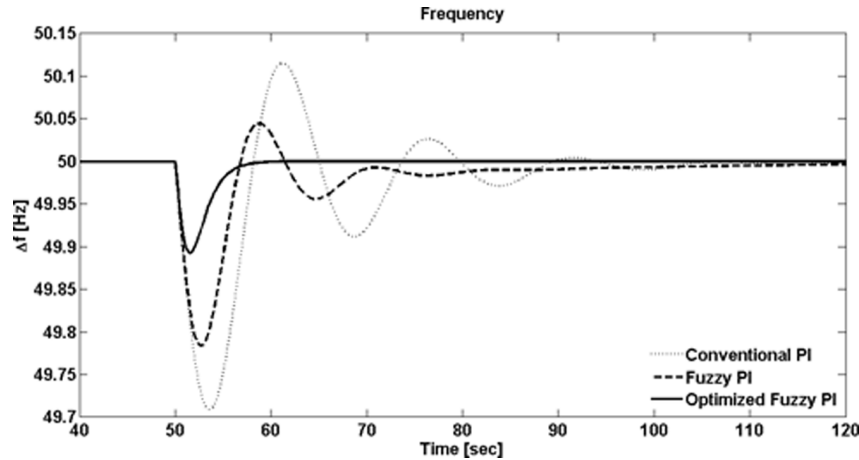
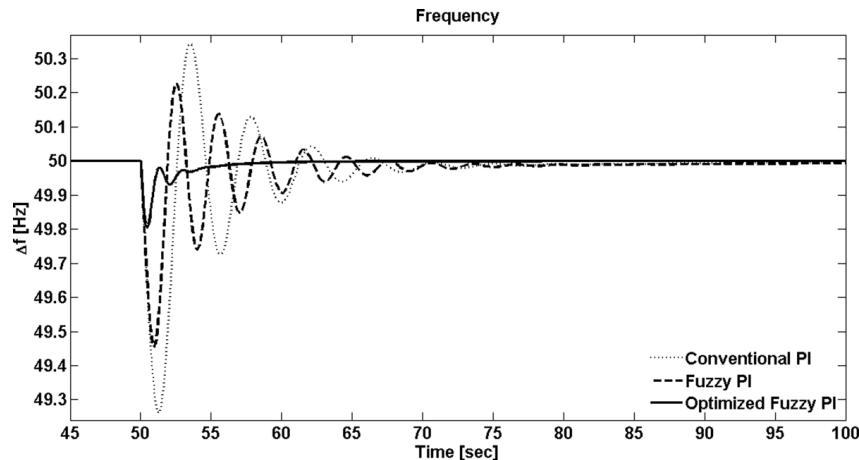


Figure 12. Frequency response under the condition of 60% changes



ROBUSTNESS AGAINST PARAMETERS VARIATION

The MG parameters are constantly changing and, this may degrade the closed-loop system performance, seriously. As indicated in the previous sections, one of the main advantages of the intelligent control methods is robustness against environmental and dynamical changes. For showing the adaptive property of the PSO-fuzzy PI controller, some system parameters, in the frequency response model (Figure 3), i.e., the time constants of the FESS, BESS and system transfer functions are significantly changed. At the first and the second scenario, the MG performance is studied under changes of 60% and 20%, respectively. The closed-loop frequency response after applying these changes to the MG system parameters, are shown in Figures 11 and 12, respectively. Figure 11 shows the difference between the proposed optimal PSO-fuzzy PI controller with the others. It can be seen from Figure 12 that the proposed method has a better performance than the other controllers, although the fuzzy PI controller has a better operation in comparison with the conventional one.

FUTURE RESEARCH DIRECTIONS

Restructuring, introducing new uncertainty and variability by a significant number of DGs, RESs and Microgrids into power systems adds new economic and technical challenges associated with synthesis and analysis frequency control in both power systems and Microgrids. A key aspect is how to handle changes in topology caused by switching in the network and how to make a robust frequency control system which able to take advantage of the potential flexibility of distributed energy resources.

A more complete dynamic frequency response model is needed in order to frequency control analysis and synthesis in Microgrid systems with

a high degree of DG/RES penetration. A proper dynamic modeling and aggregation of the distributed generating units, for frequency regulation studies, is a key issue to understand the dynamic impact of distributed resources and simulate the frequency functions in new environment.

Since the coming power in a Microgrid from some DGs/RESs, specifically wind turbine is stochastic; still it is difficult to use their kinetic energy storage in frequency control, straightly. Further studies are needed to coordinate the timing and the size of the kinetic energy discharge with the characteristics of conventional generating plants.

The Microgrids of tomorrow must be able to handle complex interactions between interconnections, distributed generating equipment and RESs, fluctuations in generating capacity and some types of controllable demand, while maintaining security of supply. These efforts are directed at developing computing techniques, intelligent control, and monitoring/measurement technologies to achieve optimal performance. Advanced computing algorithm and fast hardware measurement devices are also needed to realize optimal/intelligent frequency control schemes for Microgrids in modern power systems.

Moreover, further study is needed to define new grid codes for contribution of Microgrid (connected to the transmission system) to overall power system frequency control issue. The new grid codes should clearly impose the requirements on the regulation capabilities of the active power produced by microgrids and distributed sources.

DISCUSSION

The variability and uncertainty are two major attributes of variable DGs that notably impact on optimum power flow, power quality, voltage and frequency control, system economics, and load dispatch in the MG as well as the main grid. Integration of DGs into MG systems may increase

uncertainties during abnormal operation and introduces several technical implications and opens important questions, as to whether the traditional control approaches to operation in the MGs are still adequate. The main question arises is what happens to the frequency regulation requirements in an MG if numerous DGs are added.

The present work can be considered as an effort to response above questions. Although, often all types of DGs are not available in a typical MG, but here to provide a comprehensive case study and to analyze the frequency response of various microsources, almost all kind of DGs are considered. It is shown that an effective frequency control (such as PSO-fuzzy PI control) performs a major role in managing short-term fluctuation of variable renewable power. Without intelligent control and regulation systems, it may be very difficult to integrate large number of DGs into the MGs. For this purpose in practice, the intelligent meters, devices, and communication standards should be firstly prepared to enable flexible matching of generation and load.

This work is mainly focused on the frequency regulation problem in the isolated ac MGs from a technical point of view. The key aspect in the present book chapter is how to handle changes in topology caused by switching in the network and how to make the frequency control system robust and able to take advantage of the potential flexibility of distributed MGs and energy resources. The contribution of DGs in the frequency control task in an MG refers to the ability of these units to regulate their power output, either by disconnecting a part of generation or by an appropriate control action. Further works are needed to address economic, environmental, and other important technical issues for the MGs in both connection and disconnection operating modes. In the following, some of these issues are briefly pointed out:

As the electric industry seeks to reliably integrate numerous MGs into the bulk power system in new environment, considerable effort

will be needed to accommodate and effectively manage these unique operating and planning characteristics. Since the coming power from some DGs, such as wind turbine is stochastic; still it is difficult to use their kinetic energy storage in frequency control, effectively. Further studies are needed to coordinate the timing and the size of the kinetic energy discharge with the characteristics of other DG units.

Most significant components in the intelligent frequency control system of the future will thus be systems for metering, controlling, regulating, and monitoring indices, allowing the resources of the MG to be used effectively in terms of both economics and operability. To achieve this vision, the future frequency control systems must include advanced monitoring, processing, communications, and information technology.

Further study is needed to define new grid codes and standards for contribution of MGs (connected to the main grid) to the overall frequency control as well as other ancillary services, and for investigation of their behavior in case of abnormal operating conditions in electric network. In this respect, reliability-focused equipment standards must be also further developed to facilitate the reliable integration of additional MGs into the bulk power system. From a bulk power system reliability perspective, a set of interconnection procedures and standards are required which applies equally to all MGs interconnecting to the power grid. Finally, frequency performance standards compliance verification remains a major open issue for the MGs in different operation modes.

CONCLUSION

In this chapter, a brief review on the Microgrids concept, history and the augments for their presence in today's power systems is given. The necessity of controlling these networks is highlighted and different control categories are

introduced. Frequency control in a Microgrid in the presence of uncertainties, load changes, and sever disturbances is emphasized.

Considering poor control performance of the classical controllers in these circumstances, an adaptive/optimal control method has been used to control the frequency in an isolated Microgrid. This controller has two levels including a classical PI controller and a fuzzy system, which is used to tune the coefficients of the PI controller during the operation. Because of dependency of a fuzzy system performance to its membership functions, the particle swarm optimization algorithm is used to improve the membership function parameters. The results of simulation in the SIMULINK/MATLAB environment demonstrated the optimum performance of the proposed control techniques in comparison with the classical methods.

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KEY TERMS AND DEFINITIONS

Adaptive Control: A class of self-tuning control, where the controller parameter(s)/gain is automatically tuned to track the control objective(s).

Distributed Generation (DG): DG is defined as small-scale electricity generation by micro-sources such as wind turbine, diesel generator, and solar unit.

Frequency Control: This control can be used to stabilize the power system frequency, and to remove the steady state frequency error and restore the system frequency, following a fault/disturbance.

Fuzzy Logic: Fuzzy logic is an approach to computing based on *degrees of truth* rather than the usual *true or false* Boolean logic on which the modern computer is based. The idea of fuzzy logic was first introduced by Dr. Lotfi Zadeh.

Microgrid: A Microgrid is a localized grouping of small power generators, energy storage, and loads that can normally operate either connected to the main traditional centralized grid or in islanded mode. In islanded/disconnected mode, the Microgrid can function autonomously.

Particle Swarm Optimization (PSO): 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.

Proportional-Integral (PI) Control: The PI control is a control loop feedback mechanism widely used in industrial control systems. A PI is the most commonly used feedback controller in power systems which attempts to minimize the error by adjusting the process control inputs. The PI controller involves two separate constant parameters, the proportional, and the integral values, denoted by P and I.

Renewable Energy: Renewable energy is energy which comes from natural resources such as sunlight, wind, rain, tides, and geothermal heat, which are renewable (naturally replenished), that is constantly and rapidly renewed by natural processes.

APPENDIX

Figure 13. The graphical abstract of the proposed method

