Management of Autonomous Microgrids Using Multi-Agent Based Online Optimized NF-PID Controller

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In this paper, an adaptive multi-agent based online-tuned PID controller using Neuro-Fuzzy (NF) is proposed for dynamic management of Distributed Generations (DGs) in an autonomous microgrid. Increasing system stability and decreasing generation costs are the main aims of the proposed management strategy. Instead of one centralized management system, the management and control function is allocated to several autonomous units which are known as agents. The proposed management system is composed of fixed and variable units. The fixed variables are the three parameters (K_p, K_i and K_d) of the conventional PID controller which are adjusted based on load variation pattern in offline mode. The parameters ($\Delta K_p, \Delta K_i$) of variable unit is generated by neuro-fuzzy system. The load pattern is applied to system in offline mode and agent's optimizing units optimize the system performance. Distributed multi-agent model is considered for tuning the neuro-fuzzy parameters, whereas agents establish with neighboring agents. In autonomous mode of the microgrid, the variable units, after tuning, control the system frequency and manage energy generation of DGs, beside fixed units, in an online manner. In the study system, various kinds of DGs including wind turbine, photovoltaic, synchronous generator, and fuel cell are considered. Linear transfer function models are obtained for each DG unit. In order to achieve a better performance of the proposed management strategy the modified Particle Swarm Optimization (MPSO) algorithm is applied for tuning of the NF based PID (NF-PID) controller parameters. Simulation results in various conditions of microgrid confirm the good performance of the proposed multi-agent management strategy in comparison to the other existing methods.

keywords: *Adaptive multi agent, Optimal controller, Distributed control, MPSO, Microgrid management.*

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1. INTRODUCTION

Due to global warming, environmental carbon emissions and increasing prices of fossil fuels, Distributed Generations (DGs) have become one of the main power generation units of interest [1]. Generally, DGs include small-scale power generation resource such as wind power, solar photovoltaic, landfill gas, etc; those are located close to loads. The generated electric power using DGs is a reliable, efficient, and environmentally friendly alternative for conventional energy production from fossil fuels. However, using DGs has arisen many challenges in power systems [2]. Moreover, full benefits of DG units are gained if they can operate in both grid-connected and islanded (autonomous) modes. Hence, microgrid concept was suggested to overcome problems associated with individual installation and autonomous operation of DGs [3].

A microgrid is a part of a power system which includes multiple DG units, storage devices and loads that can operate in both grid-connected and islanded (autonomous) modes [4].A technical challenge in enabling a microgrid to remain operational in both grid-connected and islanded modes is that the DGs should be equipped with appropriate controllers accommodating both modes of operation and the transition process between the two modes. In grid-connected mode, the grid dominantly dictates frequency and voltage at the point of common coupling (PCC) of the microgrid, and the DGs control their exchanged real and reactive power components with conventional methods [5]. However, the main problem in microgrid with a various types of DGs is its stable operation in autonomous condition [6]. Although the energy storage in the microgrid can improve system performance in autonomous operation [7], it is necessary that a suitable management and control strategy is designed for microgrid in order to maintain the voltage and frequency of system within prescribed range [8].

Table 1. Advantage and drawbacks of droop methods control [17]

Droop Methods	Advantages	Avoiding of communications
		High flexibility
		High reliability
		Different power ratings
		Free laying
	Drawbacks	Poor harmonic sharing
		Influence of system impedance
		Slow dynamic response
		Integration of renewable energies
		Coupling inductances

Various autonomous control strategies have been so far proposed in literature that can be generally categorized into three major groups, droop, centralized, and distributed control strategies [9].The control strategy for multiple DG units in an islanded microgrid, based on frequency/power and voltage/reactive power droop characteristics of each DG unit, has been reported in [10, 11]. This method is similar to control of synchronous generator in power systems. The main advantages and drawbacks of the droop methods are presented in Table 1. Moreover, to resolve the drawbacks associated with these methods, additional solutions including dynamic slopes [12], additional loop for the bandwidth [13], virtual impedance [14], harmonic droop coefficients [15], additional loop with grid impedance estimation [13], and nonlinear droop control [16]have been proposed. However, these methods do not directly incorporate load dynamics in the control loop. Thus, large and/or fast load changes can result in either a poor dynamic response or even voltage/frequency instability [17].

In centralized control methods, all data of DGs and loads are sent to a centralized processor. The centralized processor analyzes all received data based on network constraints and objectives. Then, the optimal results and decision are sent to loads and DGs [18]. These methods have drawbacks including high communication costs, large data transfer, low degree of freedom, needed reprogramming in microgrid development, and complex problem solving [19].

Microgrid control using distributed control strategy was first proposed in [20]. Afterwards, several methods were proposed in this filed [21].In these methods, each agent is controlled by a local controller by receiving only local signals. Therefore, loads and DGs have the greatest degree of freedom in distributed control techniques. In addition, in the smart grids, the agents can communicate with each other. Independence in agents' operations, the impact of each agent in the environment, low cost of communication, low size of computing, and easy development are among the main advantages of distributed control methods [22–24]. Thus, it can be said that these methods are more appropriate for microgrid management with small capacity generators [25]. Nevertheless, distributed control methods have a number of drawbacks namely high probability of instability and non-optimal response to system dynamics [17].

In this paper, to overcome drawbacks of the above controllers, an optimal Neuro-Fuzzy PID (NF-PID) controller for management system based on distributed multi-agent strategy is proposed to dynamically manage microgrids with various types of DGs. The proposed management system controller is composed of fixed unit with K_p, K_i and K_d parameters and variable unit consist of ΔK_p and ΔK_i. The fixed unit parameters are adjusted based on load variation pattern in offline mode. But, the variable unit parameters are generated as the online manner by neuro-fuzzy system. In order to apply the proposed manager strategy, the microgrid components including; wind turbine, photovoltaic, fuel cell, and synchronous generator have been modeled as a transfer function. The rotational speed of the wind turbine and consequently its power output are modeled and controlled via manipulation of blades' pitch angle (at a constant generator torque).In order to optimal tune of the NF-PID controller parameters in each DG, the modified particles optimization algorithm is considered. The parameters of controllers are tuned based on switching of large loads in an offline approach. In the optimization process, each agent communicates with neighboring agents, and optimizes its own controller parameters for reduction of its frequency fluctuations and the neighbors' frequency in the presence of load variations. Various, conditions including large switching of loads, the outage of line with connected loads, outage of a DG, and different wind speed conditions are considered in order to investigate the efficiencies of our proposed controller.

In summary, the main contributions of this paper are as bellow:

• Designing online neuro fuzzy multi-agent based management strategy for various DGs in autonomous operation of microgrid which is ensures network stability and minimizes generation costs.

• Modeling the wind turbine, fuel cell, and PV system as first, second, or third-order transfer function;

• Considering generation cost of DGs and stability parameters of microgrid as a cost function for islanded management;

• Selecting appropriate optimization algorithms by analyzing various algorithms.

The proposed dynamic multi-agent-based management strategy is applied to a test microgrid system composed of wind, PV, fuel cell, synchronous generator, and loads. For all generators, linear mathematical models are used to analyze the dynamic behavior of the studied microgrid. Simulation results illustrate the efficiencies of our proposed management strategy in terms of improving stability and profit of the microgrid components.

2. TEST SYSTEM

A single-line diagram of the studied microgrid system in this paper is shown in Fig. 1. All details are available in [26]. This test system consists of radial distribution system which is connected to the utility grid through a 24.9 kV line. The 2.5MVA substation transformer is configured in delta configuration at the high voltage side and grounded Y at the low voltage side. The microgrid contains seven DG units including; wind turbine, fuel cell, photovoltaic and synchronous generators. DG1 is a photovoltaic system which is connected to bus number 848. An asynchronous 300 kW wind turbine is located on bus 822. DG3 is a fuel cell system and all of other DGs are synchronous generators with excitation and governor control system. Fuel cell and photovoltaic systems are voltage source converter based DG system controlled by active/reactive control strategy system.

Electrical parameters of distributed generation and transformers are given in appendix A. All microgrid lines are modeled

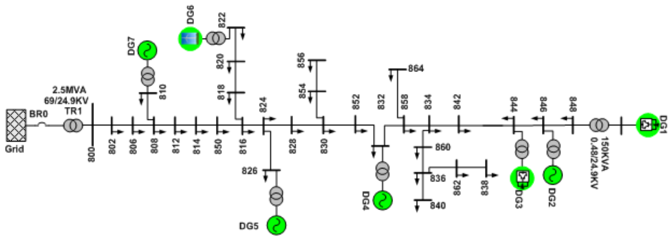

Fig. 1. Case study microgrid system

with a series resistance and impedance model. According to 34-bus IEEE load data which is given in [26], load flow results in the absence of the DGs are given in Fig. 2. As can be seen, the phase angle of buses' voltages are negligible. In dynamic modeling of the system, which is described in the next section, phases of buses' voltages are considered to be zero.

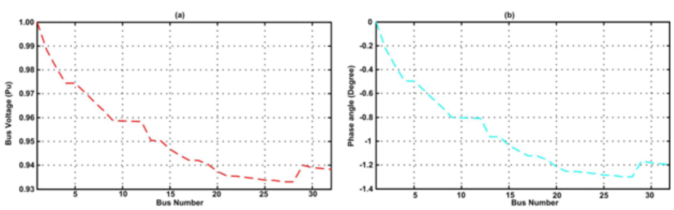

Fig. 2. load flow results of case study 34 buses power system a) voltage magnitude [19] b) phase angels of busses voltage (degree)

3. DYNAMIC MODELING

In this section dynamic models for the wind turbine PV are introduced. The model is used to perform simulations in MATLAB/SIMULINK. The synchronous generator model, which is given in [27] is used in the study system.

A. Wind Turbine model

The obtained power from wind turbine can be expressed as follows [28]:

$$P_a = \frac{1}{2}\rho\pi R^2 C_p(\lambda,\beta)V^3 \tag{1}$$

where, P_a is the obtained mechanical power for turbine blades, ρ the air density, V the speed, 4 rotational radius, the pitch angle of turbine blades, $C_p(\lambda,\beta)$ Wind turbine power coefficient and λ tip speed ratio in terms of the turbine rotational speed. Using equation (1), torque of wind turbine is determined as:

$$T_a = \frac{P_a}{\omega_r} = \frac{1}{2\lambda}\rho\pi R^3 C_p(\lambda,\beta)V^2 \tag{2}$$

By applying the torque of T_a, wind turbine will rotate by speed of ω_r. Moreover, if T_g and T_e are generator torque applied from the gearbox and load torque, the generator shaft will rotate with ω_g [29]. Generally, the turbine and generator dynamics can be expressed by equation (3)-(5).

$$T_a - T_m = J_r\ddot{\theta}_r + C_r\dot{\theta}_r + K_r\theta_r \tag{3}$$

$$T_P - T_e = J_g\ddot{\theta}_g + C_g\dot{\theta}_g + K_g\theta_g \tag{4}$$

$$T_P\dot{\theta}_g = T_m\dot{\theta}_r \tag{5}$$

where, J, C and K are inertia moment, damping factor and torsion stiffness factor of the shaft, respectively. Subscripts r and g show rotor and stator parameters and γ factor is determined as follows:

$$\gamma = \frac{\omega_g}{\omega_r} \tag{6}$$

Substituting this equation into (4) and (5), characteristic equation $T_a - \theta_r$ can be obtained as:

$$T_a - T_g = J_t\ddot{\theta}_r + C_t\dot{\theta}_r + K_t\theta_r \tag{7}$$

In this paper, T_g is considered to be constant and equal to $\bar{T}_g$. Therefore, by considering $u = T_a - \bar{T}_g$, the equation (7) can be rewritten as follows [30]:

$$u = J_t\ddot{\theta}_r + C_t\dot{\theta}_r + K_t\theta_r \tag{8}$$

Finally, the transfer function of wind turbine system is expressed as:

$$G_{WT}(s) = \frac{P_{WT}(s)}{U(s)} = \frac{\bar{T}_g s}{J_t s^2 + C_t s + K_t} \tag{9}$$

Because T_g is considered to be constant and $P_{WT} = \bar{T}_g\omega_r$, the output power can be controlled by controlling ω_r. The proposed model for a wind turbine is shown in Fig. 3.

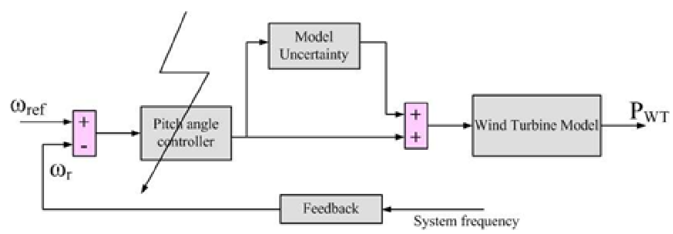

Fig. 3. load flow results of case study 34 buses power system a) voltage magnitude [19] b) phase angels of busses voltage (degree)

B. Photovoltaic system model

The output power of a photovoltaic system is defined as [31]:

$$P_{PV} = \eta S\Phi(1 - 0.005(T_a + 25)) \tag{10}$$

where, S is area of panels, η is Energy conversion efficiency of panels which is considered 12%, Φ is sun irradiation and T_a is temperature in Celsius. Energy efficiency and area of panels are constant and the output power of panels is dependent on temperature and sun irradiation. In this paper air temperature is considered 25°C and the output power is controled by variation of Φ which varies with the angle panel. In order to study the frequency response, each solar cell and converter can be modeled by the first order transfer function as follow:

$$\frac{P_{PVT}}{\Phi} = \frac{K_{PV}}{1+sT_{PV}}\frac{K_{IN}}{1+sT_{IN}} \tag{11}$$

where, P_{PVT} is the output power of a photovoltaic system, K_{PV} and T_{PV} are the gain and time constant of PV, and K_{IN} and T_{IN} are the gain and time constant of inverter, respectively. The parameters of PV system are given in [25].

C. fuel cell system model

Fuel cell consists of a cathode and an anode electrode with a Proton-Conducting as an electrolyte among electrodes. Hydrogen gas (H2) and Oxygen (O2) applies to the end of the anode and cathode plate, respectively. The fuel cell has nonlinear characteristics, but a third-order model of the system is sufficient to study the frequency response [32]. This model can be approximated as follows:

$$\frac{P_{FC}}{U_{A\&C}} = \frac{1}{1+sT_{FC}}\frac{K_{IN}}{1+sT_{IN}}\frac{1}{1+sT_{IC}} \quad (12)$$

where, P_{FC} is the fuel cell output power, $U_{A\&C}$ is the anode and cathode plate pressure, T_{FC}, T_{IC} and T_{IN} are the time constant of fuel cell, interconnection device and inverter model. As it can be seen, P_{FC} can be controlled by variations of $U_{A\&C}$. The model of PV system and fuel cell are shown in Fig 4.

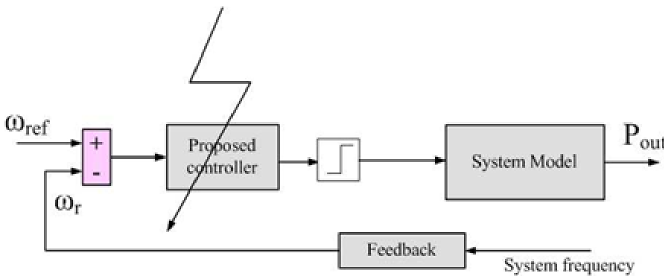

Fig. 4. PV system and fuel cell model

4. THE PROPOSED METHOD

In this paper, an optimal fuzzy multi-agent control strategy using distributed control methods is designed for autonomous operation of microgrids. Limited exchanged data, suitable transient response, low computational complexity, low implementation costs, and easy development of microgrid are some of the advantages of our proposed strategy in comparison with those of previous studies.

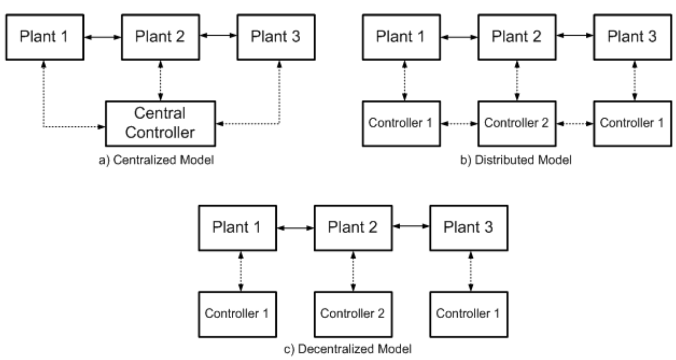

Fig. 5. Multi-agent system models a) Centralized model b) Distributed model c) Decentralized model

A. control structures using multi agent system

In general, multi-agent control methods are employed in models wherein the dynamics of each agent depends on agent's own state and set of its neighboring agents states [33]. According to this statement, the multi-agent control models can be categorized into centralized, distributed and decentralized control models [33]. Hence, we consider a general multi-agent system model as follows:

$$\dot{x}_i = f\left(x_i, \cup_{j\in N_i} x_j, u_i\right) \quad (13)$$

where, x_i and u_i are the state and inputs of agent i and N_i is the neighbor set of agent i. In this paper, analysis is restricted to static graphs. Based on used multi-agent control model, the control signal may depend on the states of the agent itself and its neighboring agent. Therefore, u_i is defined for centralized, distributed and decentralized as:

$$u_i = \begin{cases} u_i(\cup_{j\in\lambda} x_j) \\ u_i(x_i, \cup_{j\in N_i} x_j) \\ u_i(x_i) \end{cases} \quad (14)$$

In our proposed method, a distributed multi-agent model is used for controller selection and tuning of its parameters. This model is applied offline to the study system. After designing the controller, system operates in a decentralized manner. In the next section, formulation of system as a multi-agent model is described.

B. system modeling based on multi-agent structure

Electrical power systems can be considered as multi-agent systems as they often cover a large geographical area [34]. Each bus is often considered as an agent, although the dynamics of each bus is very complex, it may be well approximated by the swing equation as follow:

$$M_i\ddot{\delta}_i + D_i\dot{\delta}_i = -\sum_{j\in N_i} P_{ij} + P_{in} - P_{Li} \quad (15)$$

where δ_i and δ_j are voltage angles of i^{th} and j^{th} buses, M_i and D_i are inertia and damping coefficients, P_{Li}, P_{in} are the load power and the generated power at bus i, and P_{ij} is power exchange between i^{th} and j^{th} buses, which is determined as:

$$P_{ij} = |V_i| \sum_{j\in N_i} \left|V_j\right| \left|Y_{ij}\right| \left(\cos(\theta_L) - \cos(\theta_L + \delta_i - \delta_j)\right) \quad (16)$$

where, $|V_i|$ and $\left|V_j\right|$ are i^{th} and j^{th} bus voltage amplitudes, and θ_L is the line impedance angle which is defined as $\theta_L^{ij} = \tan^{-1}\left(X_{ij}/R_{ij}\right)$.

In the busses with no DG, the value of P_{in} is considered zero. Moreover, these busses are modeled as a frequency model and the value of M_i is also set to zero.

C. The proposed multi-agent system design

In the proposed controller scheme, each DG is considered as an agent, which is composed of two sections namely PID and neuro fuzzy based ΔPI. The PID unit parameters are determined optimally in a offline manner. The variable unit parameters, which are proposed to improve dynamic performance of system, are tuned using neuro-fuzzy system an online manner. The proposed multi-agent model has a decentralized scheme which is illustrated in Fig 5c. The PID and neuro-fuzzy system parameters are optimized by the optimizers unit in an offline distributed manner. The optimal values of parameters are delivered to the controller unit to control the system frequency optimally. The considered objective function of power system is defined as:

$$FC_t = \frac{1}{N}\sum_{i=1}^{N} FC_i \tag{17}$$

where, FC_t and FC_i are objective function values of the whole system and i^{th} agent, respectively. N is the number of agents. Each agent calculates its own cost function, which is composed of generation cost and dynamic cost, for load variation of all busses (see Fig 6) as follows:

$$FC_i = \underbrace{\int_0^{tsim} t.\left(|\Delta\omega_i| + \sum_{\substack{=1\\ \neq j}}^{K}\left|\Delta\omega_j\right|\right).dt}_{\text{DynamicCost}} + \underbrace{c_i\,|u_i|}_{\text{GenerationCost}} \tag{18}$$

where, $|\Delta\omega_i|$ is frequency variation of i^{th} agent, K the number of neighbors of i^{th} agent, time, simulation time, u_i the generated power, and c_i the cost of generated power of i^{th} agent per 100Kw.Agent Transfer Vector (ATV), which is composed of all agents' cost function values and is transferred between agents during the optimization of system parameters, is defined as:

$$ATV = \begin{bmatrix} FC_1 & FC_2 & FC_3 & \cdots & FC_N \end{bmatrix} \tag{19}$$

The expressed objective function is optimized under some constraints. The production constraint of DGs in microgrid is presented in (21). The minimum and maximum value of designing parameters is given in (22).

$$P^t_{G_{i,\min}} \leq P^t_{G_i} \leq P^t_{G_{i,\max}} \tag{20}$$

$$X_i^{\min} \leq X_i \leq X_i^{\max} \tag{21}$$

In our proposed method, an offline approach is used to optimize parameters of agents' controllers. In first step, the variable unit of controllers is inactive. In order to tune the fixed unit of the controller, the agent i, starting from $i = 1$ to N in the sequence, receives the ATV from its neighbor and updates its control parameters in each iteration during optimization. Then, the system is simulated by applying load variation of Fig. 6 to calculate of the cost function (FC_t). The obtained value of the cost function is compared with its value before updating controller parameters. If the obtained value of FC_i is smaller, it is substituted in ATV. This procedure is iterated for agents $i = 1$ to N until the variation of the cost function decreases to a predefined threshold. This procedure is shown in Fig 7. In the next step, the same stages are applied to tune neuro-fuzzy parameters of the variable unit controller.

The implementation steps of the proposed management algorithm for designing the controller can be summarized as follows:

Step 1: Selecting the initial value for controller parameters of each agent by their own optimizing unit.

Step 2: Simulating the system for load variation of Fig 6, to calculate each agent's cost function, and creating ATV for the microgrid.

Step 3: Updating i^{th} agent controller parameters based on the optimization algorithm and applying them to the system.

Step 4: Calculating FC_i and FC_t by i^{th} agent, updating ATV and i^{th} agent controller parameters, and sending ATV to the neighboring agent.

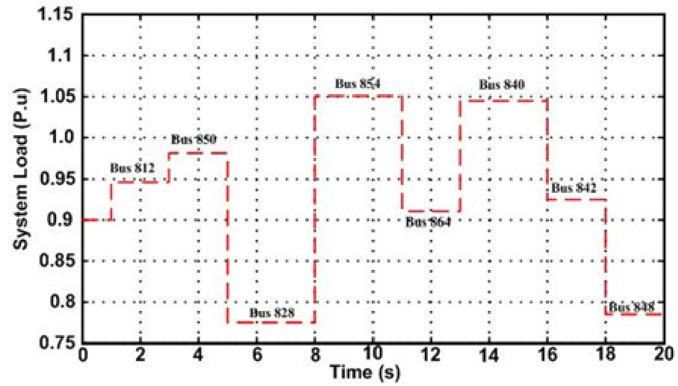

Fig. 6. Microgrid load variation in order to determine optimal controller parameters

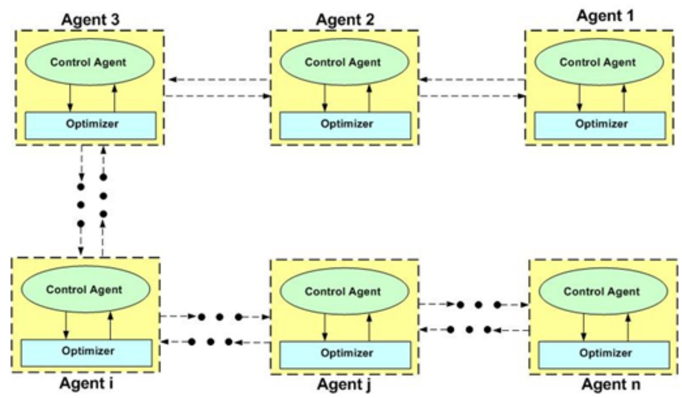

Fig. 7. Agent communication method and series controller design structure

Step 5: Repeating steps 3 and 4 for each microgrid agent.

Step 6: Repeating steps 3 to 5 until finishing the iterations of the optimization algorithm.

Step 7: Selecting optimal parameters for fixed unit of controllers and applying them to the system.

Step 8: Repeating all the steps for tuning neuro-fuzzy parameters of the variable unit of the controller.

D. Optimization method and controller model determining

The proposed structure for each agent is composed of two main modules; optimizer and controller. Moreover, the controller module is composed of fixed and variable units. The fixed unit is a PID controller and variable unit is a neuro-fuzzy based PID controller. Selecting the appropriate method for the optimization and choosing the proper controller structure can affect the performance of the proposed method and there are the system operations. The optimizer unit of each agent performs the procedure of Fig. 8 using various optimization algorithms including MPSO, DE, and ACOR, and the cost function value is calculated for each algorithm. The results of these methods in comparison with previous PID method are shown in Table 2. Based on these results, the MPSO method of the proposed method has the minimum value of the cost function. In all of the algorithms, the proposed method objective function amount is less than the previous methods. Various membership functions including triangular, trapezoidal, generalized bell, Gaussian, and two Gaussian functions are applied for the Neuro-fuzzy system. The

Table 2. The cost function value for PID and fuzzy controller for the mentioned load variation

Fixed Unit Results		Fixed & Variable units results	
Algorithm	FC_t	Algorithm	FC_t
MPSO	401.5728	MPSO	224.359
DE	421.4464	DE	241.12
ACOR	439.3451	ACOR	247.271

Gaussian function is selected for Neuro-fuzzy controller based on cost function value for each membership function. The results related to optimization and controller response are shown in Table 2.

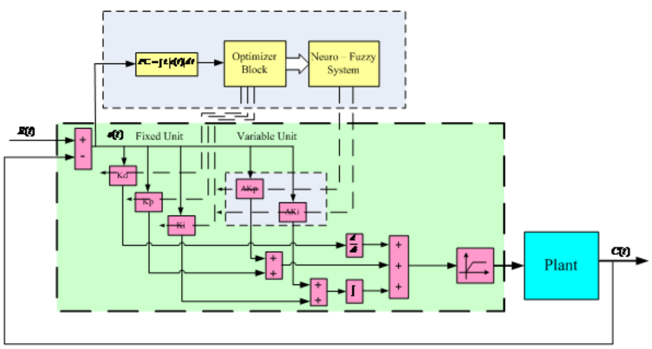

Fig. 8. Two difference model to control of microgrid agents

The selected membership function is shown in Fig . 9. The parameters of membership function are given in Tables 3, and the optimized PID values for fixed unit are given in Table 4.

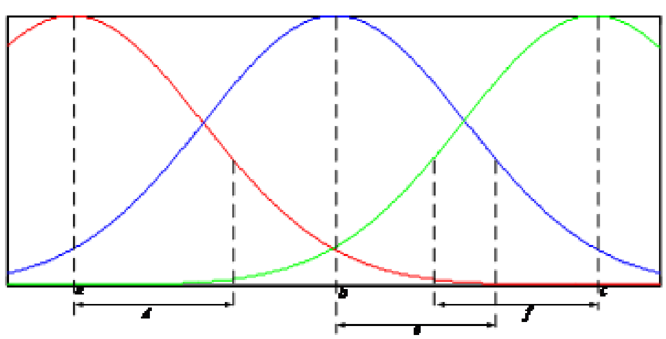

Fig. 9. The selected Gaussian membership function

5. SIMULATION RESULTS AND ANALYSIS

Several scenarios are considered to investigate the performance of the proposed control strategy in autonomous operation of the microgrid. In the islanded mode of the microgrid, several complex problems such as frequency deviation, load, and generation matching are available. To test the proposed strategy in the autonomous mode, several conditions, including load switching, variation of DG generation, and outage of DG are considered for simulations.

Table 3. The optimal membership function value of variable unitusing MPSO

	a	b	c	d	e	f
DG1	-2.32	0	1.47	5.83	2.34	5.29
DG2	-.19	0	.21	.15	.25	.28
DG3	-.01	0	.39	2.4	5.16	6.79
DG4	-.4	0	.01	4.78	3.79	5.22
DG5	-.01	0	.01	6.7	4.6	4.15
DG6	-.01	0	.4	6.07	1.21	3.25
DG7	-.01	0	.27	3.46	4.89	4.64

Table 4. The optimal fixed unit parameters value using MPSO algorithm

	Kp	Ki	Kd
DG1	14.6970	14.953	0.01160
DG2	10.5205	12.8687	0.00872
DG3	11.2177	19.0046	0.00423
DG4	12.2151	17.2423	0.00646
DG5	15.7482	21.0354	0.00853
DG6	17.8534	14.9397	0.01043
DG7	9.3479	11.5469	0.00574

A. Load increment in autonomous operation

In this scenario, the test system operates in islanded mode as shown in Fig 1, where all of active and reactive powers consumed by loads are supplied by the DG units (generation and consumption are equal). At $t = 6s$, an additional 1pu load is connected to bus 824. Frequency response of DGs and their variations in their generated power are shown in Fig 10. From Fig. 10a and Fig. 10 b, it can be seen the maximum frequency deviation and increase in generation are related to bus 826 which is nearest to bus 824. The same load switching condition is applied to bus 852 and bus 836 and the results of these conditions are depicted in Figs 11 and 12, respectively. All variations in frequency and generations are damped after 2 s, and power shortage is compensated by DGs. In Figs10-12, the performance of the proposed multi-agent management strategy is shown by applying a large disturbance in several busses of the microgrid.

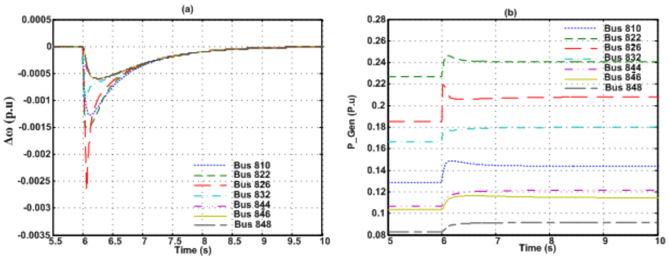

Fig. 10. simulation result related to load variation in bus 826 a) frequency response b) variations of DGs generations

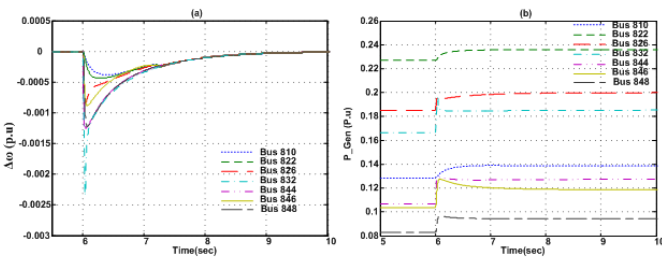

Fig. 11. simulation result related to load variation in bus 852 a) frequency response b) variations of DGs generations

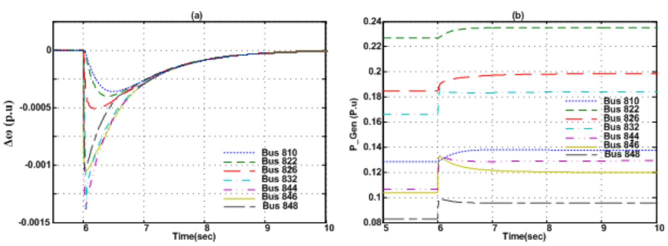

Fig. 12. simulation result related to load variation in bus 836 a) frequency response b) variations of DGs generations

B. Load decrement

In this scenario, the aim is to evaluate the performance of the proposed control strategy under the load decrement in an autonomous operation mode of the microgrid. We assume that the microgrid operates in a disconnected mode under a balanced condition (generation and consumptions are equal) and DGs feed the entire system load. At $t = 6s$ the line between bus 834 and bus 860 is tripped and all loads at busses 860, 836, 862, 838, and 840 are disconnected. The total disconnected loads from the microgrid by outage of this line are 0.164 pu. Therefore, this condition is one of the worst cases that can occur in the disconnected mode. The response of the proposed controller is shown in Fig. 13. The frequency response in Fig. 13a shows that the bus 844 and bus 832 which are nearest to the event have maximum variation, and the main reduction in power is related to these DGs (see Fig 13.b). In all the tests, system frequency remains at the allowable value and transient response is damped after 3 s.

C. Load variation in low wind speed condition

Although the output power of a wind turbine can be controlled by pitch angle, wind speed determines the maximum output power of the wind turbine. In this scenario, the maximum output power of wind turbine is limited to 1pu by considering a low wind speed. In this condition, the load variation (increase

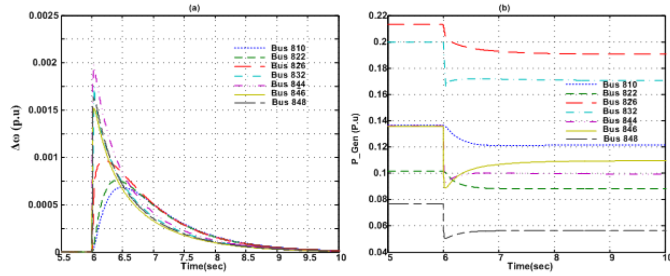

Fig. 13. simulation result related to outage of line between busses 834 and 860, a) frequency response b) variations of DGs generations

of load) of 1pu is applied to bus 824 which is close to the wind turbine. In addition, the output power of DG4 and DG5 are initially set close to nominal power which creates a critical condition in the disconnected mode. Fig 14 shows the frequency deviation and the generation of DGs related to this event. Bus 826 and bus 822 have maximum variation of frequency. Due to operation of DG4 and DG5 in nominal power, the rest of the power is compensated by other DGs. The output power of the wind turbine is limited to 0.1pu.

In the same condition, the 0.1pu load is switched on in bus 846 and the simulation results are depicted in Fig 15. It can be seen that the frequency variation in this case is less than the previous case, because this bus is close to DG1, DG2, and DG3. These simulation results show the robustness of the proposed controller against load variations even in critical conditions.

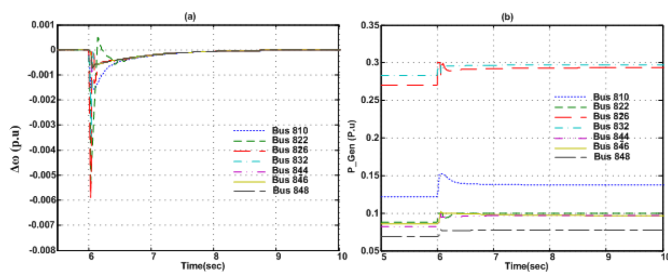

Fig. 14. simulation result related to load variation in bus 824 in low speed wind condition, a) frequency response b) variations of DGs generations

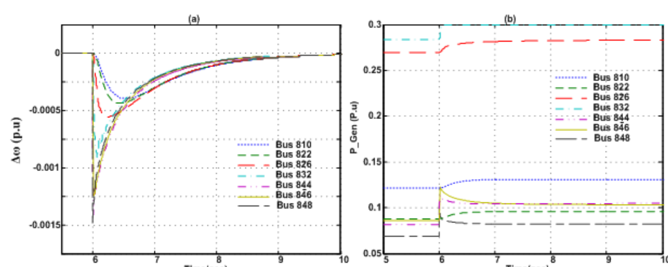

Fig. 15. simulation result related to load variation in bus 846 in low speed wind condition, a) frequency response b) variations of DGs generations

D. Outage of wind turbine DG

In the previous set of studies, the performance of the proposed control strategy in the absence of wind turbine generation has been analyzed in an islanding mode. The microgrid system initially operates in matching condition wherein the generations and consumptions are equal. In this scenario, wind generation which is one of the main power generators of microgrid, is adjusted to zero. At $t = 6s$, a 0.1pu load is connected to bus 814 which is close to the wind turbine. Since the production of wind turbine is zero, a high frequency variation (or instability condition) is expected at load switching time. The frequency variations and generations of DGs are shown in Fig 16. According to Fig 16.a, the bus 822 and bus 826, which are nearest to the connected load, have maximum variations in frequency. In comparison to other scenarios, this scenario has the worst variation that is related to the nearest generations of busses 826 and 832 in the nominal capacity before load switching. All the shortage in power is supplied by far generators DG1, DG2, and DG3. The simulation results show that in the worst condition, the proposed controller has maintained the system stability and frequency has remained within allowable ranges.

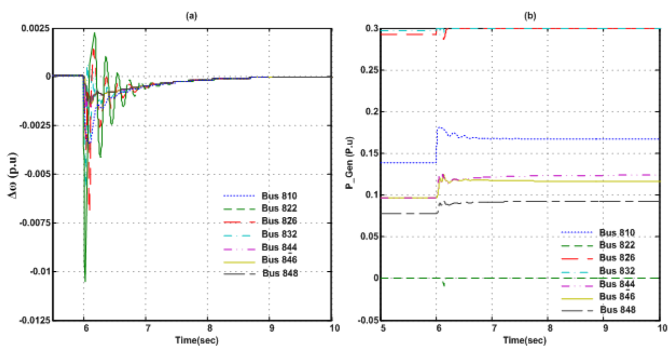

Fig. 16. simulation result related to load variation in bus 814 in outage of wind turbine condition, a) frequency response b) variations of DGs generations

6. CONCLUSION

One of the main challenges of microgrids is the control and management of distributed generations in autonomous operation. In the grid connected mode, voltage and frequency are dictated by the main grid; but in the islanded mode, the voltage and frequency should be controlled by DGs. This paper first analyzed the drawbacks of droop and central management methods. Then, the advantages of distributed multi-agent-based methods, if designed optimally, were mentioned. In order to design the performance manager for various types of DGs, a neuro-fuzzy based PID controller was proposed for microgrid generations. The proposed scheme is composed of fixed and variable parameters. In order to determine the fixed unit parameters, the load variation condition was considered and, accordingly, controller parameters were tuned in an offline manner. Also, for tuning a decentralized model was applied where each agent communicated with neighboring agents. In addition, to improve the dynamic response of system optimal neuro-fuzzy parameters are tuned as the same scheme to generate ΔK_p and ΔK_i. In order to show the performance of the proposed controller, various tests, including load variation, outage of line, outage of DG, and other switching conditions were applied to the system. In all simulation results, the frequencies of all busses remained within the allowable range. In addition, the generation of DGs in all test conditions was changed optimally.

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