Employing a Gaussian Particle Swarm Optimization method for tuning Multi Input Multi Output-fuzzy system as an integrated controller of a micro-grid with stability analysis

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Employing a Gaussian Particle Swarm Optimization method for tuning Multi Input Multi Output-fuzzy system as an integrated controller of a micro-grid with stability analysis

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Abstract

There are mainly two most essential problems in power networks, load frequency control and power flow management, which are grown recently because of growth in dimension/complication of grids. Present work suggests a controller based on fuzzy systems in which controller design is performed in a supervisory manner over a multiagent system aiming to control the frequency variation as well as generation cost minimization in the entire grid. The designing processes for low-frequency controller (LFC) and management are mostly performed separately, which results in the disruption of both outputs. This challenge is tackled in this paper by the integration of them in the designing process. Additionally, stability guarantee is in high importance in the power systems, which is neglected in most of the related works. The Gaussian particle swarm optimization (GPSO) algorithm is applied for determining the optimal values of the decision variables, which can also guarantee the stability of the system by adopting a chaotic map by Gaussian function to balance the seeking abilities of particles that promotes the computation effectiveness without affecting the efficiency of the fuzzy controller. Then, the stability situationof the fuzzy + GPSO method is derived that guarantees a suitable global exploration and rapid convergence, with no require to gradients.

KEYWORDS

GPSO, load frequency control, MIMO controller, multiagent system, power flow management

1 | INTRODUCTION

Recently, researchers are concerned about rising fossil fuel prices, increasing greenhouse gas emissions, and global warming. For solving such critical problems, renewable energy sources, and distributed generation (DG) has been proposed.[1] These systems can operate independently from the main network. Due to their intermittent nature, it is necessary to use storage systems in their structure. In the power grid, the exploitation of DGs has created several challenges.[2] Besides, the entire advantages of DGs are obtainable, in case of containing systems, the different kinds of DGs to profit merits from each power source, and once they can operate in both grid-connected and islanded (autonomous) modes. For increasing the efficiency of DGs that operate in islanded mode and individual installation, micro-grids are used.[3]

1.1 | Energy management

A micro-grid is a subset of the power grid, which includes DGs, energy storage, and loads, and operates in both grid-connected and island modes.[4] The main challenge in enabling an micro-grids (MG) is working in both stated situations. Aiming this regard, the DGs must have appropriate control systems to accommodate these two operational modes and also the transient condition between these two modes. When the micro-grid is in grid-connected mode, the network identifies the frequency and voltage in the point of common coupling, and the DG units exchange active and reactive power at these points between the grid and the micro-grid through a conventional strategy.[5] The stability of micro-grid in island mode is the most critical issue.[6] One of the storage systems benefits is to increase the MG efficiency in island conditions[7]; however, a management and control approach is proposed to maintain the voltage and frequency stability in micro-grids.[8]

Energy management is an excellent way to achieve the best performance of micro-grid, and in this way, it is necessary to ensure that the load's energy supplied by the system. The primary purpose of energy management is to provide the needed energy of loads through the micro-grid; other purpose includes increasing efficiency, minimizing operating costs, and so on. Via a central controller, the reliability of energy management is provided. In this method, all load and direct current (DC) information are directed to a centralized processor. In the next step, all data are classified according to network aim and limitations. Finally, the best result is directed to bars and DGs.[9] If this method reaches a continuous value for supplying load, it is difficult to achieve other goals, such as error reduction and reducing cost. The technique of central management is following the top-down method and needs a designer to control the system in full control of power flow, which is determined in the plan. If the event is not within the system's operating range, then the mentioned method is not responsive. Also, if any changes occur in the structure of the system, including adding or removing a component, the program should be restructured. Some of the disadvantages of central control are the high price of communication, the greatness of the transmission data, small freedom degree, need for redesign in the development of micro-grid, and complexity of the problem-solving method.[10]

For solving the problems mentioned above, the top-down approach is suggested, and the controller designer determines that each component is individually accountable. If multiple storage systems and DGs are combined, it is harder to detect the general system behavior. Energy management operates according to the top-down approach and considering the limitations of the elements. In this paper, the studied system is a multiagent system (MAS), and the mentioned method is applied to MAS. Several studies have been carried out in this field (energy management). Several definitions of energy management are defined according to the type of operation. Despite the faults and disturbances in the operating system, the proposed method minimizes cost and improves system performance. A MAS is proposed by Keshta et al[11] to achieve optimal energy management for voltage regulation and to enhance the stability of a system under different weather conditions and load perturbations for two connected micro-grids. An efficient hybrid approach is presented by Sureshkumar et al[12] for the power flow management of the hybrid renewable energy system-connected smart grid system. In the proposed approach, the control signals of the voltage source are developed by the MDA based on the variety of power exchange between the source side and load side. Like that, the online control signals are located by the backtracking search optimization algorithm procedure by utilizing the parallel execution against the active and reactive power varieties.

In the last few years, various approaches have been introduced to load frequency control of power systems. In Reference 13, micro-grid control via the distribution control approach is presented. Multiple methods for load frequency controlling are intended, which are as follows.[14] Agent control is a strategy using a local controller that receives just local signals. The highest freedom degree of distributed generators and load occurs in the distribution control approach. Also, components of smart grids can cooperate. The advantages of the mentioned method include the impartiality of factors, the impact of agents on the environment, low cost of communication, and scalability.[15-17] For controlling and managing micro-grid, comprising of low capacity DGs, the distribution tactic is one of the most suitable options.[18] Along with the advantages mentioned, the disadvantages of this method are: the high risk of instability and the system's dynamic response is not optimal.[19]

1.2 | Metaheuristic algorithms

The applications of metaheuristic approaches in engineering systems have been presented in Reference 20. A comprehensive background on metaheuristic applications, focusing on core engineering fields related to, for example, "energy," "process," and "materials." Evolutionary approaches are methods that spring from evolutionary concepts, for example, evolution programming (EP), differential evolution (DE), particle swarm optimization (PSO), and genetic algorithm (GA).[20] Khalilpourazari et al[21] proposed a novel hybrid algorithm called Sine-Cosine Whale Optimization for parameter optimization problem of the multipass milling process to minimize total production time. Pasandideh et al[22] presented a novel hybrid algorithm namely Since Cosine Crow Search Algorithm, for global optimization. Khalilpourazari et al[23] utilized a novel meta-heuristic algorithm, namely the multiobjective dragonfly algorithm, to optimize the grinding process considering a tri-objective mathematical model to simultaneous optimization of final surface quality, grinding cost, and total process time. Khalilpourazari et al[24] presented a new mathematical model for the first time, for multiitem economic order quantity for growing items considering various operational constraints. Rostamzadeh et al[25] applied the GA for performance evaluation of combined cooling, heating, and power systems. Parikhani et al[26] employed GA for obtaining the optimal thermal efficiency of a power generation system. A novel metaheuristic algorithm, namely cuckoo optimization algorithm, is designed by Sangaiah et al[27] to solve the liquefied natural gas (LNG) sales planning over a given time horizon aiming to minimize the costs of the vendor. An efficient simulated annealing (SA) is proposed to solve a multitrip vehicle routing problem with time windows specifically related to urban waste collection.[28] A Self- Learning Particle Swarm Optimization for Robust Multi-Echelon Capacitated Location-Allocation-Inventory Problem is proposed by Babaee et al.[29] Roy et al[30] introduced an algorithm and used the approach of revised multichoice goal programming to solve problems in many application areas of real-life decision-making problems. In another work, Roy et al[31] explored the study of multichoice multi-objective transportation problem (MCMTP) under the light of conic scalarizing function. In MCMTP the parameters such as cost, demand and supply are treated as multichoice parameters. Also, Reference 32 applied genetic algorithm to derive a series of optimal solutions to a rough matrix game. Das et al[33] developed two heuristic approaches to solve optimum places for the facilities and optimum transportation from.

For addressing these problems, a multiagent fuzzy controller (MIMO) is proposed to appropriate power flow in decentralized MASs. For more precise studying, the test case consists of different sources of power distribution. The MIMO method is proposed for controlling and managing the distribution systems; the factors are related to each other. The proposed scheme involves an integrated multifactor load frequency control with the aim of manage production. Because in many projects, load frequency control and management units are designed separately, so there are problems with the output of both schemes. To tackle this problem, the proposed controller includes an integrated scheme. Multiagent-based fuzzy controller parameters are arranged by the Gaussian particle swarm optimization (GPSO) method, based on obtainable load profile in a supervisory manner. The proposed test case in this paper consists of various units, including wind turbines, photovoltaic systems, fuel cells, and synchronous generators simulated by a quadratic transfer function.

The operation of the proposed system has been investigated in the event of multiple factors such as the switch of load, line exits along with loads, unit exits, and different wind speeds.

1.3 | Main contributions

1. Designing a multiagent controller based on MIMO fuzzy concept to control DGs in the micro-grid aiming to load frequency control and optimal power management in islanded mode.
2. The objective functions in this paper include the cost of generations and load frequency control in micro-grid with island mode.
3. An integrated controller is proposed for achieving the stability of the network and optimal management of the system simultaneously.
4. Optimization of the studied system by the GPSO method with a stability guarantee.
5. Analysis of the stability of the proposed controller alongside the GPSO optimization method.

In the next section, the proposed method is applied to the MAS, (micro-grid including wind turbine, solar system, fuel cell, synchronous generator, and load). The distribution system is simulated through transfer functions to investigate the dynamic performance of the power system. By examining the results, the effect of the proposed method on improving system efficiency, reducing the cost of generation and load frequency control is observed in various conditions.

2 | PROBLEM STATEMENT

In this paper, the main purpose consists of two parts. The first part reduces the frequency fluctuations for each agent, and the second part involves minimizing the cost of production for all connected systems. In this paper, the studied system is a single-line micro-grid. The single-line diagram of the studied micro-grid is shown in Figure 1. The structure of the distribution system is radial and connected to the grid via a 24.9 kV line and the 2.5 MVA substation transformer with a Δ/Y connected on the primary and secondary sides, respectively. There are two types of circuits used to maintain equal load across the three hot wires in a three-phase power system, namely

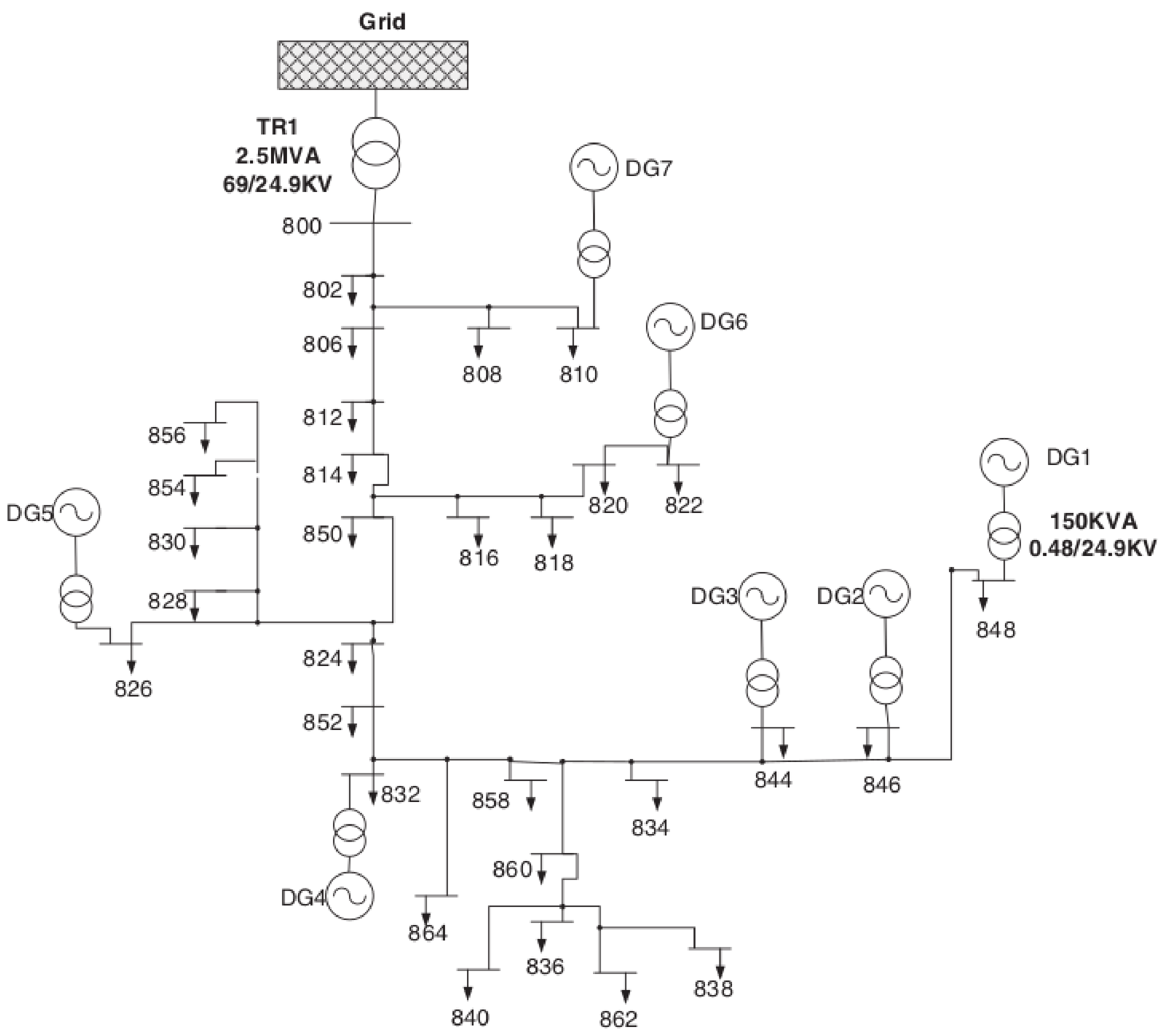

FIGURE 1 Test system micro-grid

Delta (Δ) and Wye (Y). The Delta configuration has three phases connected like a triangle. Delta systems have four wires in total: three hot wires and one ground wire. Wye systems utilize a star configuration, with all three hot wires connected at a single neutral point. One neutral wire and one ground wire make for a total of five wires in three-phase Wye systems.

The dynamic structure of load frequency control has been expanded in Reference 34. The micro-grid structure consists of seven DGs, fuel cell, solar system, synchronous generator, and wind turbine. The DG1 is connected to bus 848 is a solar system. In Bus No. 822, a wind turbine with a capacity of 300 kW is placed. Fuel cells and solar systems are the sources of DG-based voltage converter and are controlled through active and reactive control strategy system.

The data and parameters of the system studied are defined in Appendix A. All system studied lines are simulated with several series resistance and impedance. According to the power flow results of the 34-bus IEEE without the presence of DG are presented in References 34 and 35, the phase angle of the buses voltage is disregarded. Therefore, in the next section, the phase angle of the bus voltage in the dynamic simulation of the system is considered zero.

3 | DYNAMIC STRUCTURE

In Figure 1, multiagent energy management has been implemented on the system is depicted. In this system, different types of DGs are used with various capacities and features. The dynamic model and equations of solar cell and wind turbine for simulation with MATLAB software are presented in this section. In this paper, the synchronous generator model used in Reference 34 is utilized.

3.1 | Wind turbine dynamic model

The value of the output power of the wind turbine is a function in terms of wind turbine blades, density of air, rotational radius, and wind turbine power factor, which is presented as follows:

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

In the above equation, wind turbine blades, density of air, rotational radius, and wind turbine power factor are represented by P_a, ρ, $C_p(\lambda, \beta)$, respectively. The pitch angle of turbine blades is defined by β, tip speed ratio in terms of the turbine rotational speed, and speed is defined by λ and V, respectively. According to Equation (1), the wind turbine torque is obtained from Equation (2).

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

If the wind turbine torque is equal to T_a, then the rotation speed is equal to ω_r. T_g, and T_e represent the torque of the generator exerted by the gearbox and load torque, respectively. Also, the rotational speed of the generator shaft is indicated by ω_g.[25] Equations (3) and (4) express the dynamical equations of wind turbine and generators, respectively.

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

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

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

Herein, inertia moment, damping factor, and torsion stiffness factor of the shaft are expressed by J, C, and K, respectively.

The symbols r and g represent the parameters of the rotor and stator, as well as, the coefficient γ is obtained from the equation below.

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

By placing Equation (6) in Equations (4) and (5), the characteristic equation $T_a - \theta_r$ is given from the following equation.

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

In this paper, the value of T_g is assumed constant and equal to $\overline{T}_g$. Consequently, assuming $u = T_a - \overline{T}_g$, Equation (7) is rewritten as follows:

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

The wind turbine transfer function equation is obtained from the following equation.

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

Since the value of T_g is constant and according to the equation $P_{WT} = \overline{T}_g\omega_r$, the wind turbine output power is proportional to ω_r, and it is possible to control the amount of output power by changing ω_r.The wind turbine control model is shown in Figure 2.

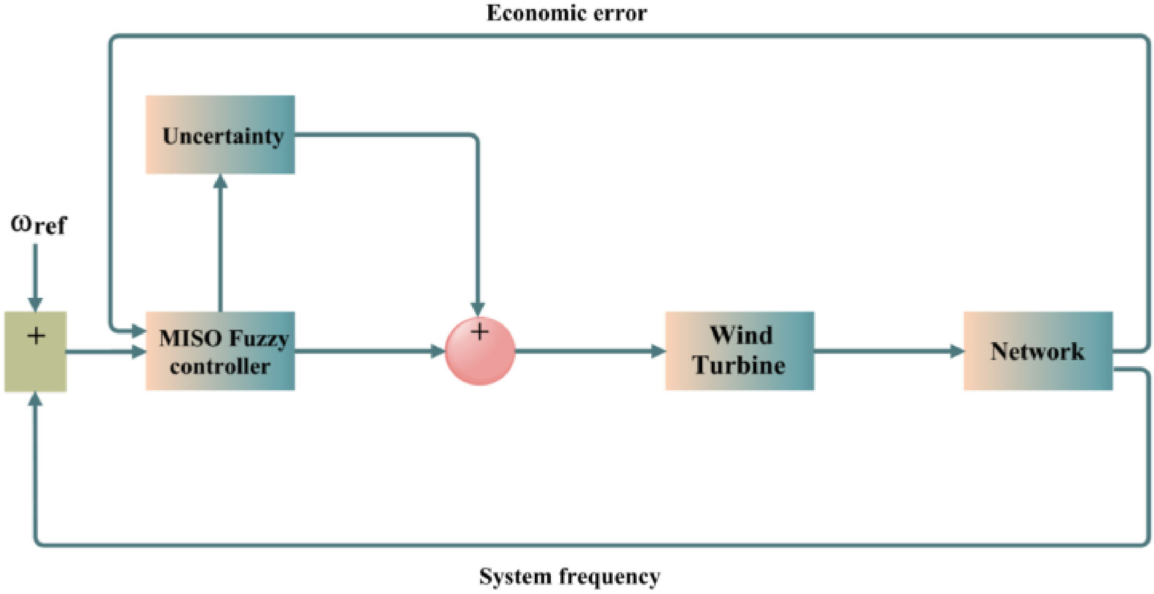

FIGURE 2 Wind turbine model with pitch angle controller [Color figure can be viewed at wileyonlinelibrary.com]

3.2 | Solar system structure

The output power of the solar system is calculated by Equation (10).[35]

$$P_{PV} = \eta S\Phi(1 - 0.005(T_e + 25)). \quad (10)$$

The electrical energy conversion coefficient by panels is shown with η, and in this paper is equal to 12%. Also, S, Φ, and T_e represent panels area, irradiation of sun, and temperature in Celsius, respectively. In this paper, the area and efficiency of panels are considered constant. On the other hand, the output power of the panels is proportional to the temperature and sun radiation. The value of Φ is proportional to the angle of panels, and the output power is also proportional to Φ and the air temperature in this paper is assumed 25 ° C. To analyze the frequency response of solar cells and converters, it is formulated using the first-order transmission function according to Equation (11).

$$\frac{P_{PVT}}{\Phi} = \frac{K_{\mathrm{PV}}}{1 + sT_{\mathrm{PV}}}\,\frac{K_{\mathrm{IN}}}{1 + sT_{\mathrm{IN}}}. \quad (11)$$

The output power of solar systems, gain, and time constant are defined with u, K_{PV}, and T_{PV}, respectively. Also, the gain and time constant of the inverter is defined with K_{IN} and T_{IN}, respectively. The details and variables of the solar system are stated in Reference 18. The solar system control model is shown in Figure 3.

3.3 | Fuel cell system structure

Figure 3 illustrates the controlling strategy of the fuel cell. The structure of the fuel cell is composed of a cathode and anode electrode via conducting proton as an electrolyte between electrodes. In the end, the cathode and anode is injected with hydrogen gas (H_2) and oxygen (O_2). The behavior of fuel cells is nonlinear, but with the approximation of the

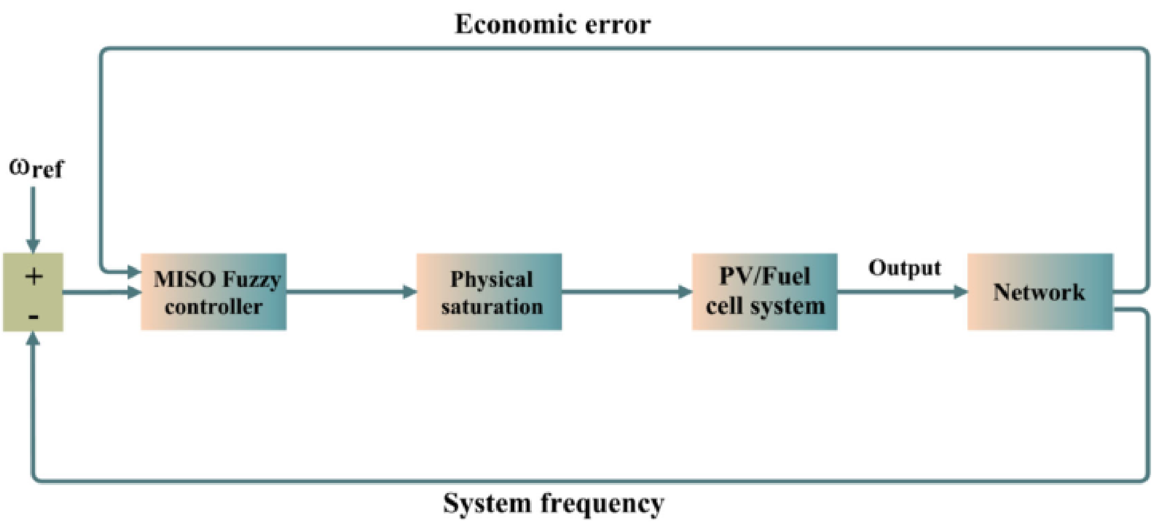

FIGURE 3 Fuel cell and photovoltaic system model [Color figure can be viewed at wileyonlinelibrary.com]

third-order model, the frequency response of the system can be studied,[36] which is expressed as follows:

$$\frac{P_{\mathrm{FC}}}{U_{\mathrm{A\&C}}} = \frac{1}{1 + sT_{\mathrm{FC}}} \frac{K_{\mathrm{IN}}}{1 + sT_{\mathrm{IN}}} \frac{1}{1 + sT_{\mathrm{IC}}}, \tag{12}$$

In this equation, the output power of the fuel cells, pressured on the cathode and anode surface is defined by P_{FC} and $U_{\mathrm{A\&C}}$, respectively. Also, the time constant of the fuel cell, interconnection equipment, and the inverter is indicated by T_{FC}, T_{IC}, and T_{IN}, respectively. Since all of the given parameters are constants, the value of P_{FC} is proportional to $U_{\mathrm{A\&C}}$.

4 | THE PROPOSED TECHNOLOGY

In this section, the multiobjective fuzzy controller optimization method (MIMO) is introduced for the controlling of the island micro-grid in the distribution system. The proposed method controls and manages the micro-grid simultaneously. The fuzzy control MIMO method has many benefits in comparison with other methods such as suitable transition conditions, low computations, little transmitted data, low establishment cost, and Comfortable expansion of micro-grid.

4.1 | Control program via MAS

Usually, in systems where the dynamics of an agent depends on other operating agent or neighboring agent, the multiagent control methodology is utilized.[37] Control methods are classified into three categories: centralized, distributed, and decentralization.[37] The general MAS equation is expressed as follows:

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

In Equation (13), x_i represents the state variables and u_i shows the inputs of the system for ith agent. N_i is the neighborhood collection for the ith agent. Only static diagrams are tested in this work. Respect to our offered control structure, the control signal can rest on states of that agent and also states of neighbor ones. For three multi-agent control approaches, the control signal is defined using the following equation.

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

In the proposed method, the distribution model is used to control and adjust the parameters. The micro-grid works in decentralized mode when the scheduling controller is sequential. In the next section, the mathematical model of the MAS is described.

4.2 | Modeling of test case based on multiagent construction

Since the power grid is developed in a large geographic area, simulation of the system is multiagent.[38] Assuming that each unit of DG is an agent, the dynamical equation of DG is formulated as follows.

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

where for the ith angle of voltage buses, the inertia and damping coefficient are defined by δ_i, M_i, and D_i, respectively. As well as, the power generation and load power for the ith agent are defined by P_{Li} and P_{in}. Injection power from bus i to bus j is represented by P_{ij} and is obtained according to the following formula.

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

Voltage bus of ith is represented by $|V_i|$, and line's impedance angle is indicated via θ_L and is equal to $\theta_L^{ij} = \tan^{-1}\left(\frac{X_{ij}}{R_{ij}}\right)$. If there are no distribution resources in the system, the size of P_{in} is zero, and are simulated as frequency model and also, the value of M_i is zero.

4.3 | Power management for the power system with the distribution model

To maximize the relative profitability of production units, the economic error is defined for DG, the lower the production efficiency rises. Although the error rate is low, the effectiveness of the production units is raised. On the other hand, the power system optimizing is due to balance the marginal prices for all buses. The total production cost for DGs is obtained by the following equation.

$$\text{Cost}_i^{\text{Gen}} = \frac{1}{2} C_i P_{\text{Gen}_i}^2. \tag{17}$$

where π represents the total power rate across the micro-grid. Profit from DG is obtained by the following equation.

$$\Omega_i = \pi P_{\text{Gen}_i} - \frac{1}{2} C_i P_{\text{Gen}_i}^2. \tag{18}$$

To maximize profits from DG is derivate from Equation (18), according to Equation (19), and then equal to zero.

$$\frac{\partial \Omega_i}{\partial P_{\text{Gen}_i}} = 0 = \pi - C_i P_{\text{Gen}_i}. \tag{19}$$

In other words, according to Equation (19), the profit value of each unit of DG equals to:

$$\pi = C_i P_{\text{Gen}_i} \tag{20}$$

Equation (20) for all DG units is expanded as follows:

$$\pi = C_1 P_{\text{Gen}_1} = C_2 P_{\text{Gen}_2} = \ldots = C_n P_{\text{Gen}_n}. \tag{21}$$

The rate factor of resource generation is expressed by C_i and the amount of power generated by DG is defined by P_{Gen_i}. The produced power error by DG or the same economic error is obtained from the following equation.

$$\Delta C_i = \sum_{j \in N_i, \neq P_{j,\max}} C_j P_j - C_i P_i. \tag{22}$$

Since one of the main objectives of this paper is to minimize the cost of producing energy and balance the rate between DG and micro-grid, hence, in the next section, the economic error is considered as one of the control parameters.

4.4 | Proposed control structure

Based on the MIMO fuzzy system, the suggested model is made up of each agent. The structure of the proposed MIMO system contains two inputs and one output. According to the previous section, when the production of all generators is the same, the economic error is equal to zero, and the optimal position is obtained. The economic error mentioned in the previous section is the input of the fuzzy system, and the second input system is frequency error. The single output intended for the fuzzy system is the amount of power produced by the DG units. The general structure of the MIMO fuzzy system is defined below. To increase the efficiency of the studied system, a suitable method for optimization, and the appropriate controller is selected. To achieve the optimal amount of the fuzzy system parameters, the MOPSO algorithm is used. We chose the Gaussian function for the fuzzy system according to the objective function amount of each membership function. In Figure 4, the proposed model of the MIMO fuzzy controller system is depicted.

Since the studied system is multi-input and single-output and is a subset of MIMO, only the multi-input single output (MISO) rules are discussed in this paper. If the single-input

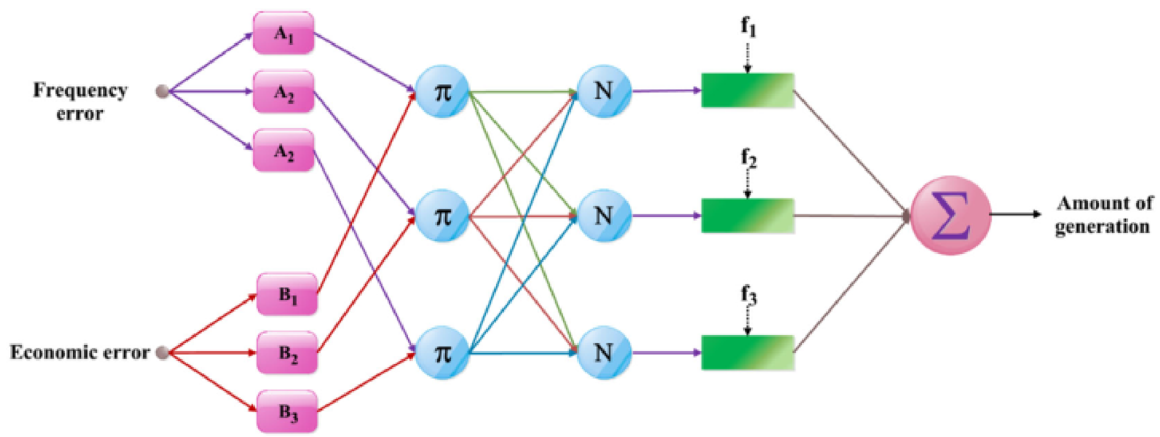

FIGURE 4 Configuration of suggested multiobjective fuzzy controller optimization method fuzzy control system [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 1 Core rule set

X1 \ X2	B1	B2	B3
A1	VL	L	M
A2	L	H	L
A3	M	L	VL

single-output fuzzy system is used, the results are affected by each other and nonoptimal results are obtained. Therefore, MISO rule is used to enhance controller stability. With the MISO method, two inputs, the economic and frequency errors, are applied simultaneously in the system and do not affect each other results.

In the MISO structure, the number of n inputs with x-rules $(x_1, x_2, \ldots, x_n)$ and n conjunctive terms in the premise are expressed as follows:

$$\{\text{Rule}(i_1, i_2, \ldots, i_n) : \text{IF } (x_1 \text{ is } N^1_{i_1}) \text{and } (x_2 \text{is } N^2_{i_2}) \text{ and} \ldots \text{.and } (x_n \text{is } N^n_{i_n}) \text{ Then } y \text{ is } Y_{i_1 i_2 \ldots i_n}\},$$

In the above relation, the jth input from the n inputs is defined by x_j and the ith linguistic term of x_j is represented by $N^j_{i_j}$. The $i_j = 0, \ldots, m_j$ specify how fine the jth input is fuzzy divided. The control vertex of Rule $(i_1, i_2, \ldots, i_n)$ is represented by $Y_{i_1 i_2 \ldots i_n}$. Using Equation (23), the output of the MISO fuzzy controller is obtained.

$$y = \frac{\sum_{i_1=0}^{m_1} \cdots \sum_{i_n=0}^{m_n} \left(Y_{i_1,\ldots,i_n} \prod_{j=1}^{n} N^j_{i_j}(x_j) \right)}{\left(\sum_{i_1=0}^{m_1} \cdots \sum_{i_n=0}^{m_n} \prod_{j=1}^{n} N^j_{i_j}(x_j) \right)}. \tag{23}$$

The real linguistic is divided into three categories: low, medium, and high, with the input variables x_1 and x_2 are classified as $\{A_1, A_2, A_3\}$ and $\{B_1, B_2, B_3\}$, respectively. It should be noted that the collection of a core rule contains nine rules, as described in Table 1. In the case of the output parameter y, the fuzzy singletons are specified to provide "VL" (very low), "L" (low), "M" (middle), and "H" (high).

4.5 | Scheming the proposed MAS model

In the suggested MAS model, agents are considered generators of distribution, and in the structure of all agents, there is a MIMO fuzzy controller. Using supervision learning, the optimal fuzzy controller parameter values are determined. In Figure 5, the proposed model of decentralized MAS is shown. Initially, the values of the MIMO fuzzy controller parameter are determined using the optimization method, and then these values are applied to the controllers for the purpose of the load frequency controller.

The dynamic cost for the oscillation of load frequency of all buses in DG units is considered as the objective function, which is defined using Equation (24).

$$\text{FC}_i = \int_0^{t\text{sim}} t. \left(|\Delta\omega_i| + \frac{1}{N_i} \sum_{j \in N_i} |\Delta\omega_j| \right) .dt. \tag{24}$$

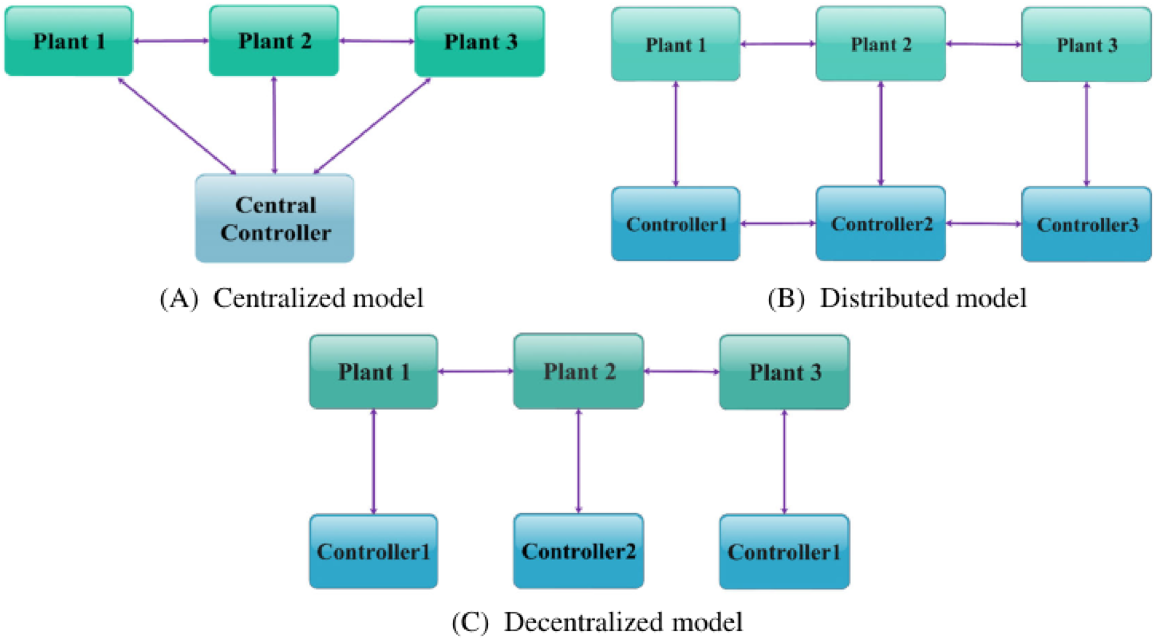

FIGURE 5 Different types of MAS. A, Centralized model. B, Distributed model. C, Decentralized model [Color figure can be viewed at wileyonlinelibrary.com]

where $|\Delta\omega_i|$, N_i represent the amount of frequency oscillation in bus i and the number of neighbors for bus i, respectively. As well as time and the needed time for simulation is denoted by t and sim, respectively. Given the N_{ag} agent, the cost function of the entire micro-grid is obtained using the below equation.

$$\text{FC}_t = \int_0^{t\text{sim}} \frac{1}{N_{\text{ag}}} \sum_{i \in N_{ag}} t. \left(|\Delta\omega_i| + \frac{1}{N_i} \sum_{j \in N_i} |\Delta\omega_j| \right) .dt. \tag{25}$$

As already stated, the parameter values are obtained via the optimization method, which considering a few limitations. One of the constraints is expressed in Equation (26), which indicates energy constraint. In the energy management section, the limitation of boundary rate equalization is defined via Equation (27). The oscillation range of the parameters is shown in Equation (28).

$$P^t_{G_i,\min} \leq P^t_{G_i} \leq P^t_{G_i,\max}. \tag{26}$$

$$\sum_{j \in N_i, \neq P_j \max} C_j P_j - C_i P_i = 0. \tag{27}$$

$$X_i^{\min} \leq X_i \leq X_i^{\max}. \tag{28}$$

Using the supervisory optimization technique, the controller parameters are obtained. Initially, to optimize parameters, an initial value is assumed for all the MIMO controller variables. In the next step, to calculate the cost function FC_t, the presented load in Figure 6 applies to the

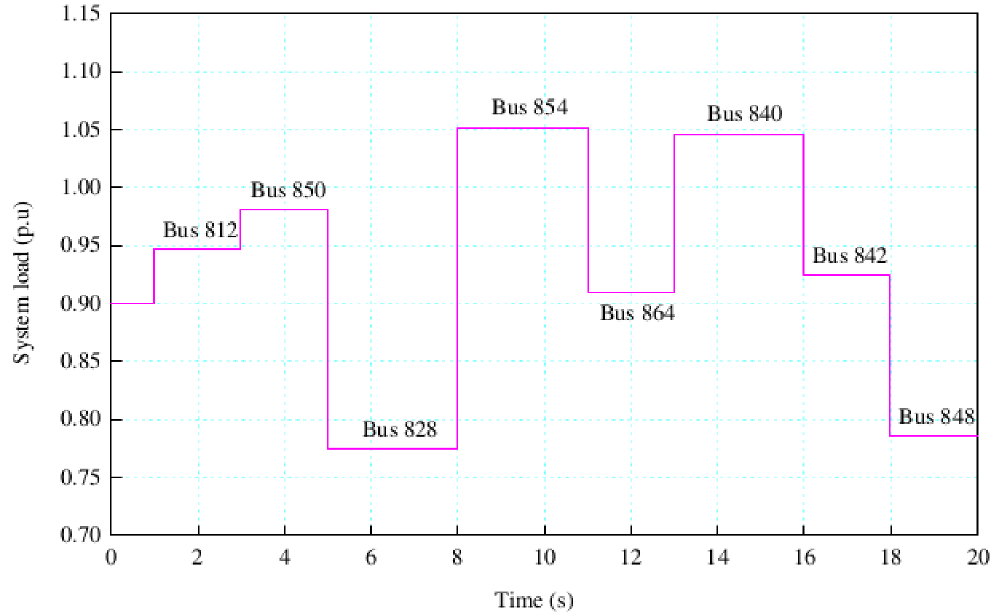

FIGURE 6 Load oscillation of system for specification of optimum coefficients of control system [Color figure can be viewed at wileyonlinelibrary.com]

simulated system. Also, the results obtained from the objective function are compared with the results before the changing parameters. This procedure continues until the fluctuation of the objective function parameters reaches the specified range. The remarked load profile is implemented on simulated plant in offline way for optimization the variables of control system. Although the agents are related to neighboring agents, the parameters are optimally with supervisory manner. At the same time, in micro-grid island mode, the frequency and manages the power generated are controlled through resources, and the micro-grid performance in distribution mode.

First, the optimization parameters are determined, and then the optimization method is implemented. As mentioned in the previous section, the MIMO fuzzy controller parameters should be optimized. Since there are two inputs in this paper and the number of fuzzy rules is 3, then there are in total six rules for all inputs. In this paper, Gaussian membership has been used, and since there are two parameters for each rule, there are a total of 12 parameters in the input. On the other hand, the output of fuzzy systems consists of nine fuzzy controllers. As a result, a total of $9 + 12 = 21$ is considered an optimization parameter for each DG. The structure of studied micro-grid includes seven DG; as a result, in total 147 optimization variables exist. Among different learning methods, according to the optimization variable, optimization problems are solved using the GPSO algorithm. In Figure 7, the structure of the problem is shown by the optimization of the GPSO algorithm.

5 | PROPOSED GPSO METHOD AND STABILITY ANALYSIS

The configuration of the GPSO method is represented in this part of the paper. Primarily, an adaptive inertia weight is presented as the iterative steps grow. Then, a chaos random trajectory improved section with Gaussian function proportions is furthered to accelerate the updating relation. Finally, the stability of this method, in addition to fuzzy + GPSO, is guaranteed by the

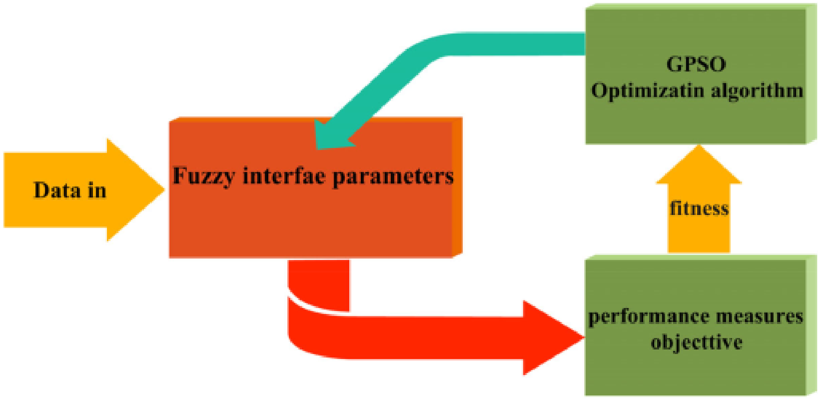

FIGURE 7 Configuration of fuzzy + Gaussian particle swarm optimization control system [Color figure can be viewed at wileyonlinelibrary.com]

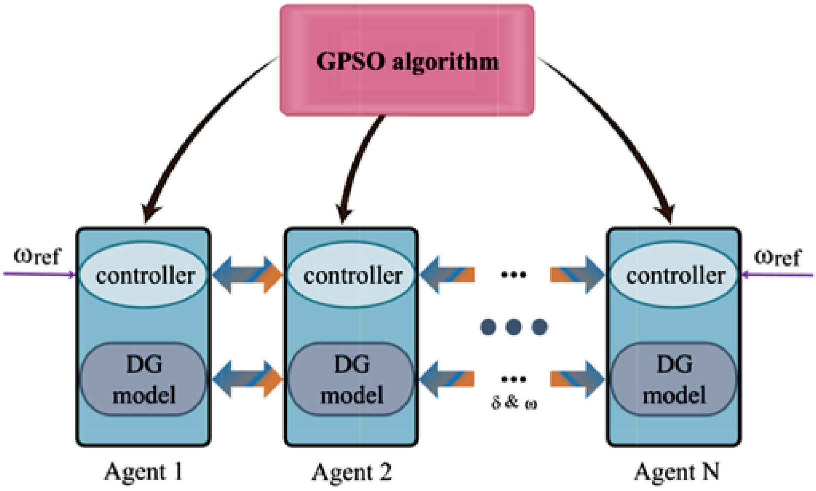

FIGURE 8 Agent communication approach and series control system design construction [Color figure can be viewed at wileyonlinelibrary.com]

Lyapunov function. In Figure 8, agent communication approach and series control system design construction is illustrated.

5.1 | Particle swarm optimization algorithm

PSO inspired by the bird's behavior.[39] This method has four major variables that are determined in the next: the position of the swarm is indicated by $x_i = \{x_{i1}, x_{i2}, \dots, x_{iD}\}$, in which min and max amounts for them are determined by $x_{id} \in [x_{\min,\,d}, x_{\max,\,d}]$ where $d = 1, 2, \dots, D$. The best solution of particle i in the prior step is indicated by $p_i = (p_{i1}, p_{i2}, \dots, p_{iD})$. Also, the velocity in the present step assumed to be $v_i = (v_{i1}, v_{i2}, \dots, v_{iD})$ that is bounded in range of $[v_{\min}, v_{\max}]$. Location of best solution from the population is determined by p_{gbest} as $p_g = (p_{g1}, p_{g2}, \dots, p_{gD})$. Afterward, updating of velocity and location of particles toward their p_{best} and p_{gbest} can be done by:

$$\begin{cases} v_{id}(k+1) = wv_{id}(k) + c_1\text{rand}_{1d}[p_{id}(k) - x_{id}(k)] + c_2\text{rand}_{2D}[p_{gd}(k) - x_{id}(k)], \\ x_{id}(k+1) = x_{id}(k) + v_{id}(k+1) \end{cases} \tag{29}$$

In this equation, w which is inertia weight takes value in the interval $[0-1]$ and indicates how much of prior parameters are maintained; parameters of rand_{1d}, rand_{2d} denote evenly spread random numbers in the interval [0 to 1] in which a random amount is selected for all dimensions. Moreover, c_1, c_2 determine acceleration coefficients.

5.2 | GPSO and its stability analysis

This part of the paper depicts the framework of GPSO method that divided into two following edited sections:

1. Inertia weights are considered as an adaptive parameter.
2. Second part introduces a random chaos trajectory using Gaussian function proportions that are furthered to speed up updating relations. Also, the stability of the GPSO is proofed by a Lyapunov approach.

The GPSO method has a high ability to search optimal points with a proper computational burden. The main phases of this algorithm are shown in Table 2. The following sections describe all highlighted main parts of this table. Furthermore, the stage of bounding updated velocity is just utilized for fuzzy + GPSO that is elaborated in the next part.

5.2.1 | Adaptive inertia weight

Inertia weight is utilized for controlling of prior velocity history effect on present velocity. Moreover, compromising among global and regional seeking capability of particles is determined

TABLE 2 Pseudocode for Gaussian particle swarm optimization (PSO)

Start
  Initialize the population
  Validate the objective values; $f(x)$
  Update the P_i and P_g
  While (stop criteria = false)
   do
    Update inertia weight $w()$
    For ($i = 1$ to individuals' number)
     For ($d = 1$ to dimensions' number)
      Update the velocity and location arrays
      (bound the new velocity () – – – just for fuzzy + GPSO)
      Augment d
     End For
      Validate the objective values; $f(x)$
      Update the P_i and P_g
     For ($d = 1$ to dimensions' number)
      Compute the chaotic sequence and orbit improved location ()
      If $x_{id} > x_{\max}$, $x_{id} = x_{\max,d}$
      If $x_{id} < x_{\max}$, $x_{id} = x_{\min,d}$
       Augment d
     End For
    Augment i
   End For
  End while
End

by inertial weight. Large value of this parameter can help to global search, whereas small value can lead to facilitate local search like fine-tuning present exploration region. A proper amount of this parameter mostly causes equilibrium among global search and local search potentials. Subsequently, it leads to the decrement of needed iterations for the finding of the optimal answer.

In this paper, nonlinear manners proposed for adaptively setting of inertia weight w. A determined w is just proper for one parameter setting, and it's not essentially consistent with remain parameters. Therefore, this suggested approach will set various parameters equivalent to different w_d. Following that, cost function $e(k)$ of the PSO method is evermore a lumpy multimodal curve. Once convergence of the PSO algorithm is to the more steady surface of the cost function, it will be consecutive iterations. It translates that a symbol of $\delta_d(k) = \partial E(k)/\partial x_d(k)$ will not vary. So, $w_d(k)$ can be augmented for decrement of iterations number across the flat section that is shown in Equation (30). If convergence is to a concave plane, $\delta_d(k) = \partial E(k)/\partial x_d(k)$ can be changed. For avoiding from divergence in this algorithm, $w_d(k)$ must properly dwindled. Once the iterations number grows, the amount of adaptive inertia weight will reduce gently in the following form:

$$w_d(k) = \begin{cases} w_d(k-1) + \cos\left(\frac{\text{iter}-1}{\text{maxiter}-1} * \frac{\pi}{2}\right) & \delta_d(k-1)\delta_d(k) > 0 \\ w_d(k-1) * \cos\left(\frac{\text{iter}-1}{\text{maxiter}-1} * \frac{\pi}{2}\right) & \delta_d(k-1)\delta_d(k) < 0 \\ w_d(k-1) & \text{else} \end{cases}, \tag{30}$$

In which, the present iteration and max iteration number are expressed respectively by iter and Maxiter. Using this formula, the inertia weight can be set adaptively in various steps in the exploration procedure with no need for previous knowledge. This can promote efficiency impact among global and regional optimization ability.

5.2.2 | Gaussian function and chaotic map

For preventing untimely convergence in PSO and also being proper for fuzzy parameter optimization, PSO exploration must adaptively shift from prophase global exploration to a later local approximate search. There exist two factors in Gaussian function, including mean c and variance σ.

$$f(x;\sigma,c) = e^{-\frac{(x-c)^2}{2\sigma^2}}, \tag{31}$$

where the mean and location p_{gbest} are equal, which is the fittest location from whole particles. So, it can be said; the GPSO principle is that, once particles like x_1, are more near to the best location; trajectory editions are more significant. Accordingly, the far particles from p_{gbest} like location x_2 achieve lower modification. It is due to that the optimization capabilities of particles that are neighbor to the fittest location are weak. Subsequent to Equation (29) updating location of particles, added position evolutional section is furthered in the following form:

$$x_j(k+1) = \begin{cases} x_j(k) + \alpha * h_j(k) * \|p_g(k) - x_j(k)\|_2 * (x_{\max} - x'_j(k)) & \text{if } \alpha > 0 \\ x_j(k) + \alpha * h_j(k) * \|p_g(k) - x_j(k)\|_2 * (x'_j(k) - x_{\min}) & \text{if } \alpha < 0 \end{cases}, \tag{32}$$

In which, α is a number in the range of $[-1, 1]$ that is generated by random. This parameter can guarantee the suggested GPSO to seek a positive or minor direction. Also, $h_j(k)$ indicates the presented Gaussian function, and $\|p_g(k) - x_j(k)\|_2$ signifies to space among jth particle and fittest position. Moreover, x_j' determines the chaotic parameter. Finally, the location of $x_j(k+1)$ should be bounded in the range of $[x_{\min}, x_{\max}]$. Particular scheme of Gaussian function can be represented by:

$$\begin{cases} h_j(k) = 1 & p_g(k) = x_j(k) \\ h_j(k) = e^{-\frac{(\|p_g(k) - x_j(k)\|^2)}{2\sigma^2(k)}} & p_g(k) \neq x_j(k). \end{cases} \tag{33}$$

The related variable is calculated as follows:

$$\sigma^2(k) = \sigma_0^2 e^{-\left(\frac{k}{\tau_1}\right)}. \tag{34}$$

According to Equation (33), once this particle finds the best location, the Gaussian function will be equal to 1. It translates, the next amendments do not change the trajectory of the particle. Furthermore, respect to properties of Gaussian function, adjustment of near particles to the global best location is more and the far ones from p_{gbest} have lower modification. Also, respect to Equation 33, the increment of iteration number k, leads to that Gaussian function becomes steeper gently. Therefore, the absolute of updating get more and smaller, which ensures the approximation ability of suggested GPSO in the next interval of optimization.

Besides, chaotic map (x_j') is represented in trajectory amending by:

$$z_j^{n+1} = 4z_j^n(1 - z_j^n). \tag{35}$$

$$x_j' = x_{\min} + z_j(x_{\max} - x_{\min}). \tag{36}$$

In these equations, z_j^n denotes the iterative mapping variable of chaos in which j and n are respectively size and index of particle. Moreover, lower and higher bounds of particle location are, respectively, indicated with $x_{\min}$ and $x_{\max}$. Equation (35) expresses a chaotic logistic map, a characteristic of which is that for the great part of amounts of r it's equal to 4. A chaotic model is mainly sensitive to starting situations. So, the primary amount z_j^1 is a stochastic number in range of (0, 1) but {0.25, 0.5, 0.75}. The succession z_j^n represents chaotic properties that are more appropriate compared to uneven spread in the aspect of travel ergodicity. Nevertheless, {0.25, 0.5, 0.75} values must be excepted, and it is due to that if they are selected as starting amounts, amount of z_j^n will be fixed at 0.75, 0, and 0.75, respectively. Via Equation (32), particles of untimely convergence are distributed in answer region for seeking the other areas seeking new answers. Thus, it preserves the contiguous global exploration ability and prevents becoming ambushed in local optimum solutions. We utilized Gaussian function as a declining method for regulation of the degree of chaotic map dynamically with no manual adjusting factors.

5.2.3 | Stability analysis for GPSO algorithm

The stability of this approach is analyzed by uncertain robust stability theory. Aiming this regard, relations of adaptive GPSO in this framework can be represented by:

$$\begin{bmatrix} x(k+1) \\ v(k+1) \end{bmatrix} = \begin{bmatrix} 1 & w(k) \\ 0 & w(k) \end{bmatrix} \begin{bmatrix} x(k) \\ v(k) \end{bmatrix} + \begin{bmatrix} 1 \\ 1 \end{bmatrix} u(k). \tag{37}$$

$$y(k) = [1 \ \ 0]\begin{bmatrix} x(k) \\ v(k) \end{bmatrix}. \tag{38}$$

$$u(k) = -\phi(k)(y(k) - p). \tag{39}$$

In which control signal is represented by $u(k)$ and $\phi(k)$ can be calculated by $\phi(k) = c_1\text{rand}_1 + c_2\text{rand}_2$. Moreover, p determines the balance point $x_* = p$, $v_* = 0$ that can be calculated by:

$$p = \frac{c_1\text{rand}_1 p_{id}(k) + c_2\text{rand}_2 p_{gd}(k) + \zeta(k)}{\phi(k)}. \tag{40}$$

It can be seen, with the growth of iteration number, Gaussian edition section $\zeta \rightarrow 0$ and once the swarm proceeds to fittest answer, $p_{id}(k) = p_{gd}(k) = p$. So, p expresses the fittest answer in the optimization procedure.

For simplification of system relation, state array of $\zeta(k) = \begin{bmatrix} x(k) - p \\ v(k) \end{bmatrix}$ is presented that forces state-variables achieve the balance point, $x(k) = p$, $v(k) = 0$ well simultaneous with PSO method. Thus, the new state-space can be written in following form:

$$\zeta(k+1) = A(k)\zeta(k) + Bu(k). \tag{41}$$

$$y(k) = C\zeta(k). \tag{42}$$

$$u(k) = -\phi(k)y(k). \tag{43}$$

In these equations, state matrix, input vector and also output vector are respectively $A(k) = \begin{bmatrix} 1 & w(k) \\ 0 & w(k) \end{bmatrix}$, $B = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$ and $C = [1 \ \ 0]$. Therefore, the state-space equations can be rewritten as follows:

$$\zeta(k+1) = (A(k) - \phi(k)BC)\zeta(k). \tag{44}$$

$$(A(k) - \phi(k)BC) = \begin{bmatrix} 1 - \phi(k) & w(k) \\ -\phi(k) & w(k) \end{bmatrix} = (A_0 + \Delta A_0(k)). \tag{45}$$

Once $w(k) \neq 0$, $(A(k) - \phi(k)BC)$ will be nonsingular. Thus, just if ζ_* be equal to zero, relation $\zeta_* = (A(k) - \phi(k)BC)$ is contented. These state-space equations have a unique balance point in their origin. Matrix $(A(k) - \phi(k)BC)$ is divided into two sections including a time-invariant (TI) section A_0 and time-variant (TV) section ΔA_0 with uncertainty. So, below new scheme will be achieved:

$$(A_0 + \Delta A_0(k)) = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} + \begin{bmatrix} -\phi(k) & w(k) \\ -\phi(k) & w(k) \end{bmatrix}. \tag{46}$$

Thus, adaptive particle stability is changed into below robust stability form:

$$\zeta(k+1) = (A_0 + \Delta A_0(k))\zeta(k). \tag{47}$$

In which, the uncertain term can be stated in the form of $\Delta A_0(k) = D_0 F_0(k) G_0$, where D_0, G_0 are known real matrices with the appropriate size and $F_0(k)$ denotes unknown real TV matrix that its components are Lebesgue-measurable expressed as:

$$F^T(k)F(k) \leq I. \tag{48}$$

In the suggested GPSO method, this constraint is accidental, due to that $\phi(k)$ is a random number in the interval [0, 1], and $w(k)$ is in range of 0 to 1, in all times.[40]

Lemma. *Assume that symmetric matrix $S = S^T \in R^{(n+m)\times(n+m)}$ be represented by*[41]:

$$S = \begin{bmatrix} A & B^T \\ B & C \end{bmatrix}, \tag{49}$$

where $A \in R^{n\times n}$, $B \in R^{m\times n}$, $C \in R^{m\times m}$. Necessary and sufficient terms for $S > 0$ is as follows:

$$C > 0 \ \text{ and } \ A - B^T C^{-1} B > 0. \tag{50}$$

Lemma. *Assume D, E, and F are real matrices that have appropriate size and constraint (20) is satisfied. So, for any positive number $\varepsilon > 0$*[41,42]:

$$DFE + E^T F^T D^T \leq \varepsilon DD^T + \varepsilon^{-1} E^T E. \tag{51}$$

Theorem. *(main result): assume that adaptive particle is expressed with perturbed Equation* (47) *and uncertain section contents Equation* (48). *The represented system in Equation* (47) *is asymptotically stable in its origin point if exist a symmetric positive-definite matrix P, a scalar value ε_0 and a coefficient $\alpha > 0$, so that below linear matrix inequality satisfied*:

$$S = \begin{bmatrix} \overline{A}_0^T P + P\overline{A}_0 + 2\alpha P + \varepsilon_0 \overline{G}_0^T \overline{G}_0 & P\overline{D}_0 \\ \overline{D}_0^T P & -\varepsilon_0 I \end{bmatrix} < 0 \tag{52}$$

In this equation, $\overline{A}_0 = [A_0 + (c+r)I]^{-1}[A_0 + (c-r)I]$ and also $\Delta\overline{A}_0(t) = 2r[A_0 + (c+r)I]^{-1} \Delta A_0(t)[A_0 + (c+r)I + \Delta A_0(t)]^{-1}$.

Proof. Primarily, represented the system in Equation (47) is generated through s linear fractional transformation as:

$$w = f(s) = \frac{s+c-r}{s+c+r}. \tag{53}$$

Also, the continuous equivalent of the discrete system is in the following form:

$$\dot{\overline{\zeta}}(t) = (\overline{A}_0 + \Delta\overline{A}_0(t))\overline{\zeta}(t). \tag{54}$$

Through presenting a new state transformation $z(t) = e^{at}\overline{\zeta}(t) > 0$, the following equation, can be achieved:

$$\dot{z}(t) = ae^{at}\overline{\zeta}(t) + e^{at}\dot{\overline{\zeta}}(t) = az(t) + e^{at}(\overline{A}_0 + \Delta\overline{A}_0(t))\overline{\zeta}(t). \tag{55}$$

We assumed a Lyapunov function as:

$$V(z(t)) = z^T(t)Pz(t), \tag{56}$$

In which, P is the symmetric positive-definite matrix. The derivative of this function can be obtained as follows:

$$\begin{aligned}\dot{V}(z(t)) = \dot{z}^T(t)Pz(t) + z^T(t)P\dot{z}(t) = 2az^T(t)Pz(t) + z^T(t)(\Delta\overline{A}_0^T(t)P + P\Delta\overline{A}_0(t))z(t)\\ + z^T(t)(\overline{A}_0^T P + P\overline{A}_0)z(t).\end{aligned} \tag{57}$$

Respect to predefined $\Delta\overline{A}_0(t) = \overline{D}_0\overline{F}_0(t)\overline{G}_0$, Lemmas 1 and 2, it can be said:

$$\dot{V}(z(t)) \leq z^T(t)(\overline{A}_0^T P + P\overline{A}_0 + 2aP + \varepsilon_0^{-1}P\overline{D}_0\overline{D}_0^T P + \varepsilon_0\overline{G}_0^T\overline{G}_0)z(t) = z^T(t)Sz(t) < 0, \tag{58}$$

In which, $S = \begin{bmatrix} \overline{A}_0^T P + P\overline{A}_0 + 2\alpha P + \varepsilon_0\overline{G}_0^T\overline{G}_0 & P\overline{D}_0 \\ \overline{D}_0^T P & -\varepsilon_0 I \end{bmatrix} < 0.$

Thus, this theorem is proven. ■

5.2.4 | Stability analysis of GPSO-based fuzzy controller

Theorem. *Suppose, Theorem 1 holds, and assume that* $X(k) = \frac{v(k)}{e(k)}$, $Y(k) = \frac{d(k)}{e(k)}$. *Gaussian-based fuzzy controller has asymptotical stability in mentioned unique equilibrium point if* $|w(k)| < 1$, $w(k) \neq 0$ *and also*:

$$-2\sqrt{\frac{1}{3}} < w(k)X(k) + \phi(k)Y(k) < 2\sqrt{\frac{1}{3}}. \tag{59}$$

Proof. Let us define Lyapunov function in the form of:

$$V(k) = \frac{1}{2}e^2(k). \tag{60}$$

The error can be calculated by:

$$e(k) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(y_d(k) - y(k))^2} = \sqrt{J}. \tag{61}$$

So, Lyapunov function variation among two step times is equal to:

$$\Delta V(k) = V(k+1) - V(k) = \frac{1}{2}[e^2(k+1) - e^2(k)]. \tag{62}$$

Furthermore, error alteration can be calculated by:

$$e(k+1) = e(k) + \Delta e(k). \tag{63}$$

Also, the strictly differential equation for error can be represented by:

$$\Delta e(k) = \frac{\partial e(k)}{\partial \mu}\Delta\mu + \frac{\partial e(k)}{\partial \sigma}\Delta\sigma, \tag{64}$$

In which, μ and σ are two adjusting variables in the fuzzy system. Updating equations of these variables can be written as:

$$\Delta\mu = -\frac{\partial J}{\partial \mu} = -2e(k)\left(\frac{\partial e(k)}{\partial \mu}\right) = w(k)v^{\mu}(k) + \phi(k)d^{\mu}(k). \tag{65}$$

$$\Delta\sigma = -\frac{\partial J}{\partial \sigma} = -2e(k)\left(\frac{\partial e(k)}{\partial \sigma}\right) = w(k)v^{\sigma}(k) + \phi(k)d^{\sigma}(k). \tag{66}$$

In these relations, $w(k)$, $\phi(k)$ denote dynamic inertia weight and a random number of GPSO method, respectively; also $v^*(k)$ and $d^*(k)$ signify to a velocity of particle and space among the present location and location of the best particle in the group, respectively. Afterward, it can be found that Equation (61) is composed of circular symmetric polynomial covering of $\left(\frac{\partial e(k)}{\partial \mu}\right)^2, \left(\frac{\partial e(k)}{\partial \sigma}\right)^2$. Thus, factorization can be written as:

$$\Delta V(k) = 2e^2(k) \times \left[\left(\frac{\partial e(k)}{\partial \mu}\right)^2 + \left(\frac{\partial e(k)}{\partial \sigma}\right)^2\right] \times \left[\left(\frac{\partial e(k)}{\partial \mu}\right)^2 + \left(\frac{\partial e(k)}{\partial \sigma}\right)^2 - 1\right]. \tag{67}$$

So, obviously if

$$\left(\frac{\partial e(k)}{\partial \mu}\right)^2 + \left(\frac{\partial e(k)}{\partial \sigma}\right)^2 < 1. \tag{68}$$

So, $\Delta V(k) < 0$. Therefore, the fuzzy controller is stable. Moreover, according to circular symmetric features, sufficient terms can be scaled to [0, 1/3):

$$0 \leq [w(k)v^{\mu}(k) + \phi(k)d^{\mu}(k) < \frac{1}{3} \times 4e^2(k). \tag{69}$$

$$0 \leq [w(k)v^{\sigma}(k) + \phi(k)d^{\sigma}(k) < \frac{1}{3} \times 4e^2(k). \tag{70}$$

Regarding defined error function $J = e^2(k)$ and also defined $X(k)$ and $Y(k)$, these inequalities can be converted to the following form:

$$-2\sqrt{\frac{1}{3}} < w(k)X(k) + \phi(k)Y(k) < 2\sqrt{\frac{1}{3}}. \tag{71}$$

Thus, theorem 2 is proven. ■

Result. Velocity limits must be set dynamically:

$$v_{\min}(k) = -2\sqrt{\frac{1}{3}}e(k),\ v_{\max} = 2\sqrt{\frac{1}{3}}e(k). \tag{72}$$

GPSO-based fuzzy controller has asymptotical stability in its unique equilibrium point.

Proof. With respect to Theorem 2

$$-2\sqrt{\frac{1}{3}} < w(k)X(k) + \phi(k)Y(k) < 2\sqrt{\frac{1}{3}}. \tag{73}$$

$$-2\sqrt{\frac{1}{3}} < \frac{w(k)X(k) + \phi(k)Y(k) - p}{e(k)} < 2\sqrt{\frac{1}{3}}. \tag{74}$$

$$-2\sqrt{\frac{1}{3}} < v(k+1) < 2\sqrt{\frac{1}{3}}. \tag{75}$$

Regarding that $v(k+1) \in [v_{\min}, v_{\max}]$; thus this result is proven. ∎

As shown, velocity limits dynamically set to guarantee GPSO-based fuzzy controller stability, with no required manual adjustment. From the viewpoint of both hands in inequality (67), the amount of $e(k)$ reduces, and limits adaptively decrease. So, particles tend to stop finally.

6 | RESULTS AND DISCUSSION

Multiple positions are used to check the performance of the proposed controller in the island mode. Frequency deviation, loading, and production equilibrium are among the most important issues in the investigation of the micro-grid island mode performance. The criteria for evaluating the performance of the micro-grid in the island state are some conditions of load switching covering, offsets distribution resources, and the fluctuations in generation of distributed.

Gaussian Membership functions, which are shown in Figure 9 are utilized in this system. In addition to the previous conditions, load fluctuation is considered in island mode.

In this section, in addition to the conditions mentioned in the previous step, load fluctuations are taken into account. Then the obtained results are investigated in terms of stability and production cost.

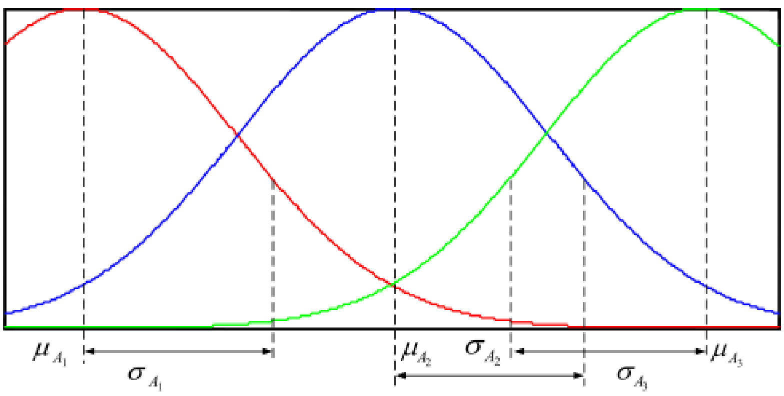

FIGURE 9 Chosen Gaussian membership function [Color figure can be viewed at wileyonlinelibrary.com]

6.1 | Load rate in the islanded state

In Figure 1, the island micro-grid is plotted along with the active and reactive power consumed in distribution units. On the other hand, the amount of production and consumption of energy is in balance. In the 816 and 854 buses, for 10 seconds, the positive disturbances load is injected as amount 0.1 p. u. At the same time, the disruption is applied to both buses so that the results of both buses are checked. The profile of frequency in the distribution system is shown by taking into account the fluctuations generated by the production of power, with energy management is shown in Figure 10. The costs mentioned and also the total costs of production for both scenarios are given in Table 3. By analyzing the results, it can be stated that the best position is selected using the proposed controller. The cost of power generation is controlled by the SISO fuzzy controller, which is only frequency control, depending on the network location and stability.

In the second step, the bus load 854 is increased to 0.1 p. u. and the effect of the controller is investigated. The amount of power produced and the frequency response of the system are shown in Figure 11. Table 4 shows the cost of generating power after applying disrupted in load. As a

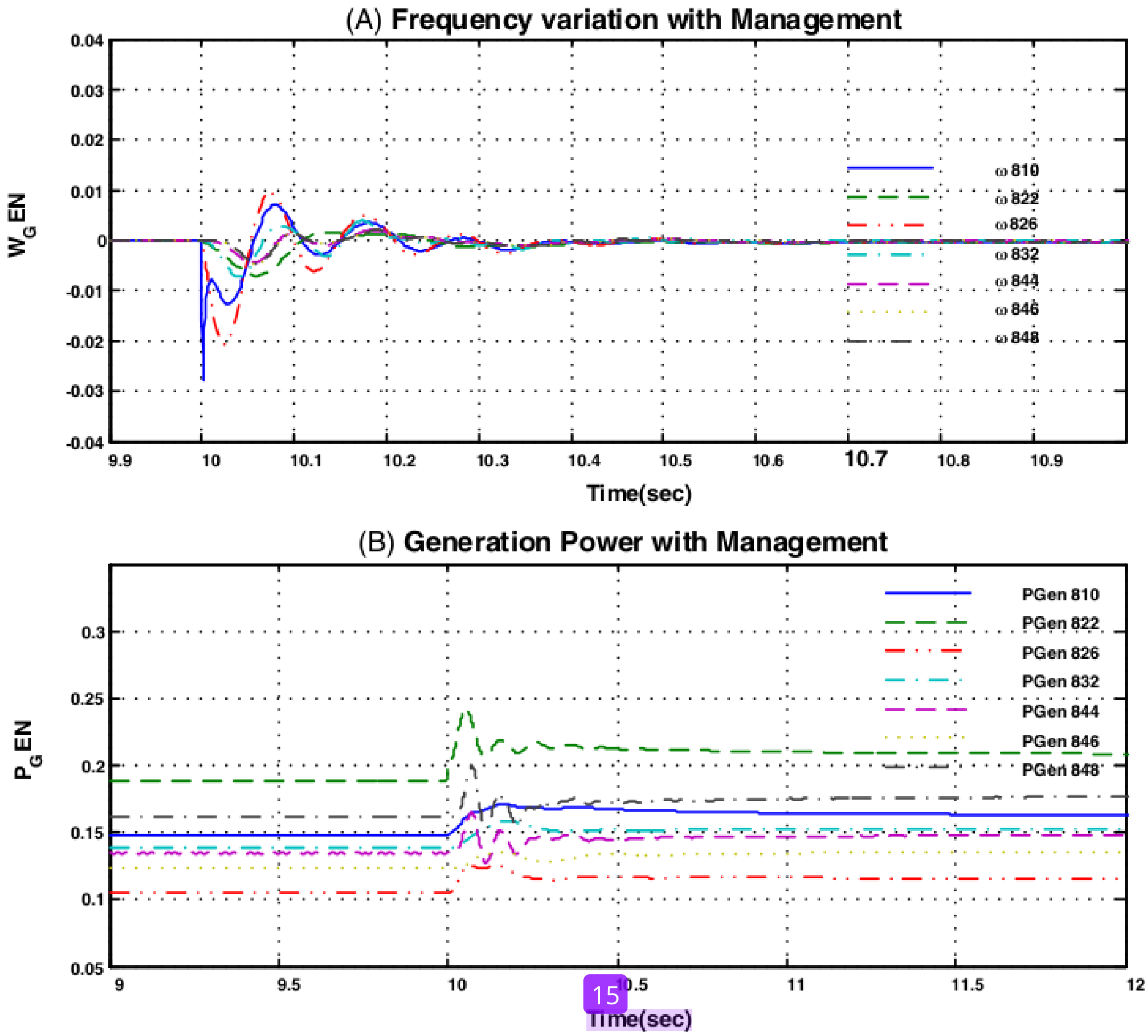

FIGURE 10 The relevant obtained results to load growth scenario in bus-816 in the presence of management input [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 3 Power production expenditure for 0.1 p. u. load growth scenario in bus-816 in presence and absence of management input

Parameters	DG810	DG822	DG826	DG832	DG844	DG846	DG848
C_i coefficient of DG	0.0031	0.0026	0.0043	0.0035	0.0034	0.0037	0.0031
Managed produced power	167.12	199.33	120.56	148.05	152.46	140.09	167.17
Unmanaged produced power	66.8	176.9	283.2	105.1	178.9	139.3	144.6
Power cost of managed mode	283.687		Power cost of unmanaged		362.08		

Abbreviation: DG, distributed generation.

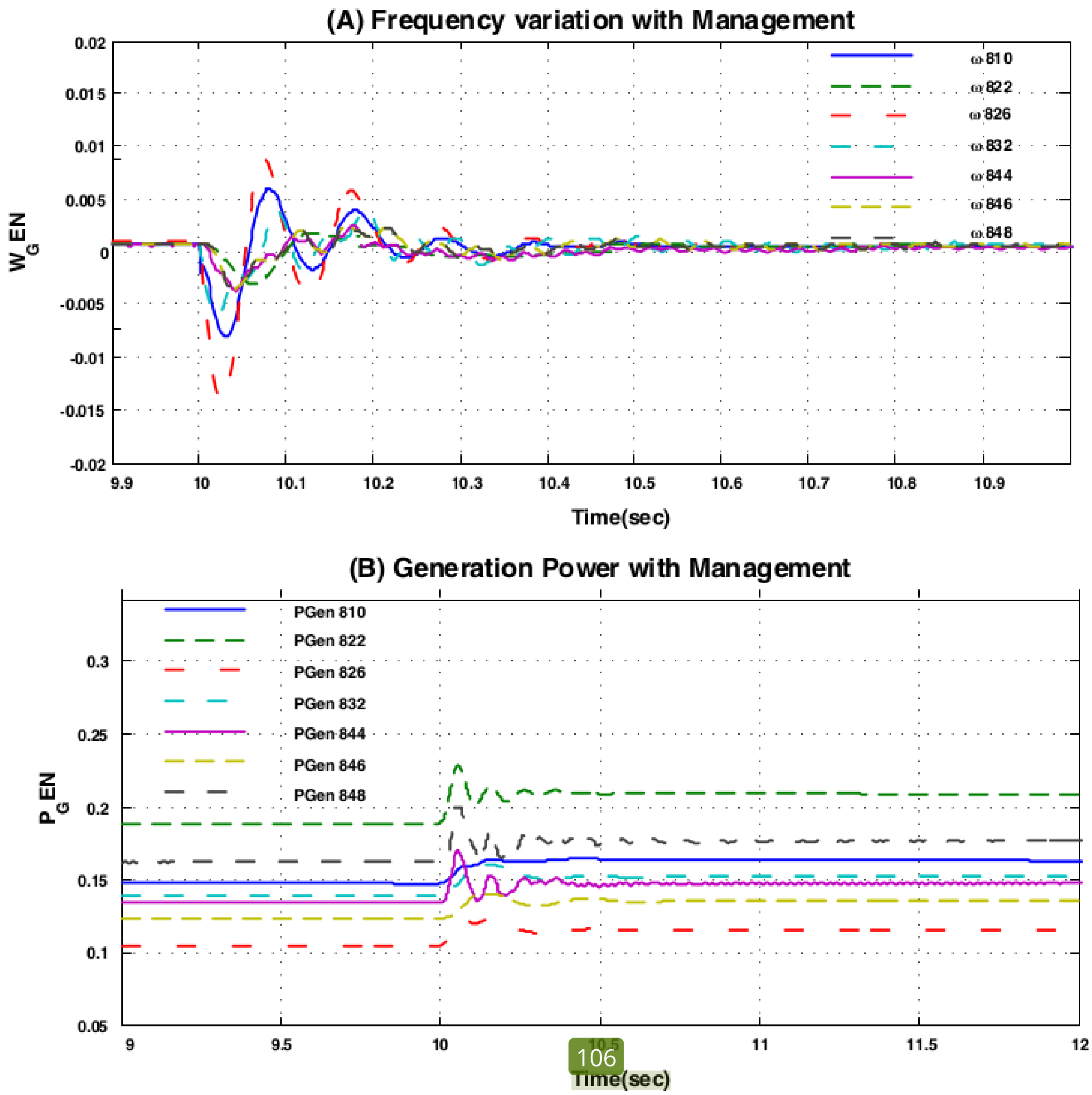

FIGURE 11 Obtained results for load growth scenario in bus-854 in the presence and absence of management input [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 4 Power production expenditure for 0.1 p. u. load growth scenario in bus-854 in presence and absence of management input

Parameters	DG810	DG822	DG826	DG832	DG844	DG846	DG848
Ci coefficient of DG	0.0031	0.0026	0.0043	0.0035	0.0034	0.0037	0.0031
Managed produced power	167.12	199.33	120.56	148.05	152.46	140.09	167.17
Unmanaged produced power	65.5	173.6	285.1	109.4	174.8	138.8	147.6
Power cost of managed mode	283.687		Power cost of unmanaged mode			362.881	

Abbreviation: DG, distributed generation.

TABLE 5 Power production expenditure in 0.08 p.u. load reduction scenario in bus-860 in presence and absence of management input

Parameters	DG810	DG822	DG826	DG832	DG844	DG846	DG848
Power cost ($/kw)	0.0031	0.0026	0.0043	0.0035	0.0034	0.0037	0.0031
Managed produced power	139.77	166.63	100.79	123.86	127.54	117.18	139.85
Unmanaged produced power	63.4	91.1	257.6	92.1	160.5	123.4	127.5
power cost of managed mode	198.434		Power cost of unmanaged mode			271.693	

Abbreviation: DG, distributed generation.

result, the controller has improved the performance of the system in terms of energy management and frequency control compared to other methods.

6.2 | Reducing the load amount

In this section, the load is reduced to 0.08 p. u. at 860 bus number. Concerning the reduction of the load, power production in terms of sustainability and management reaches a desirable point. Results are obtained using fuzzy controller MIMO and SISO are shown in Table 5 and Figure 12. Based on the results, if the load decreases, the controller will continue to work and improve system performance.

6.3 | The same energy cost for DGs

Assuming a load loss of 0.08 at 828 bus and considering the same coefficient of production about 0.003 $/kW for all DGs, the proposed controller function has been investigated. In Figure 13, the effect of the proposed controller is shown, and by examining the figure, it can be stated that the generation of energy for each DG is equal to 131.4 kW. Therefore, the energy management distribution system of the micro-grid has been implemented correctly with the proposed controller.

6.4 | Limitation on wind turbine

Due to wind speed, the turbine output is limited to 0.1 p. u. In Figure 14, the results show a positive load disruption of 0.05 p. u. at 828 bus. In Figure 14, the results of this disorder are depicted.

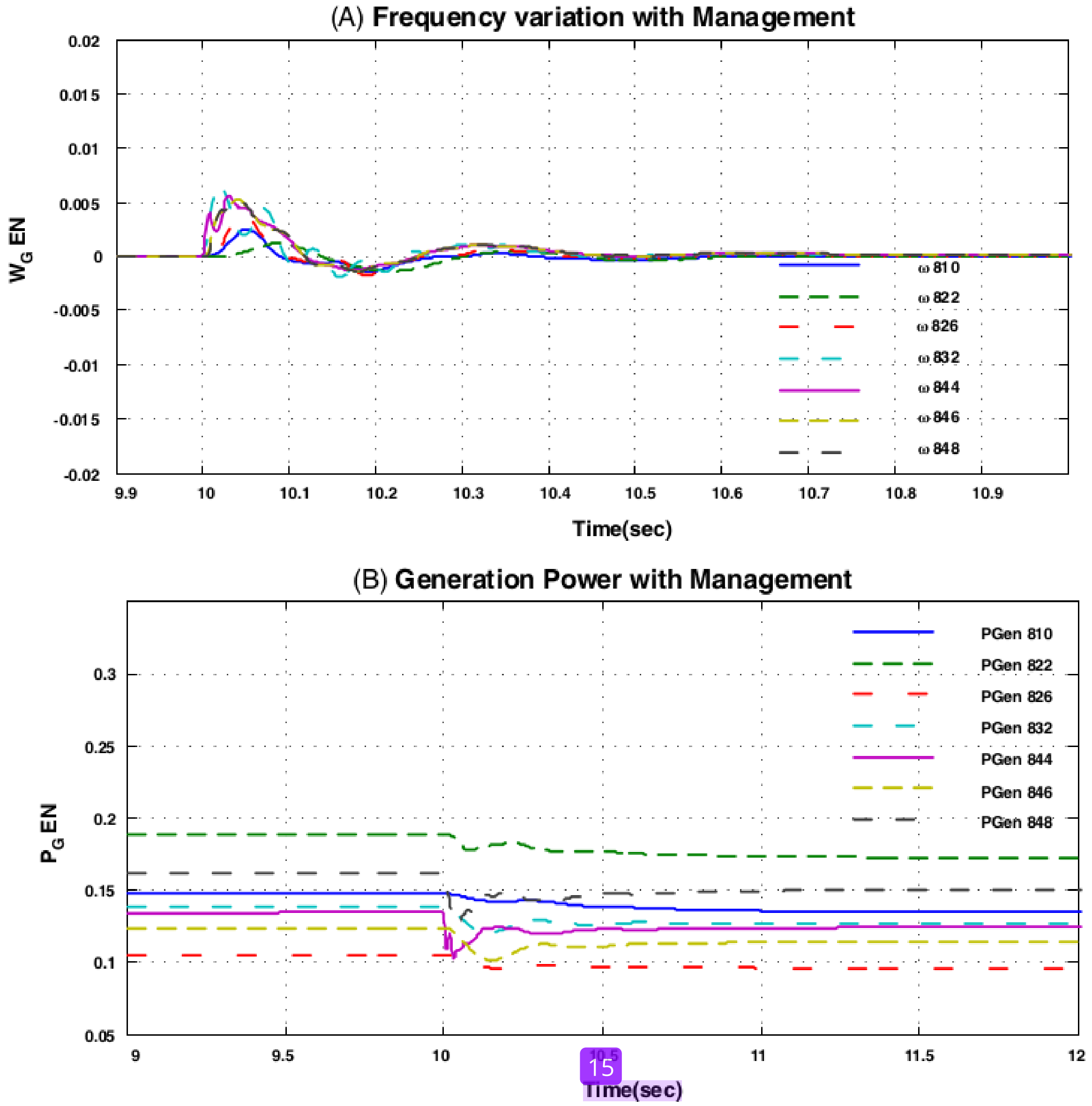

FIGURE 12 Obtained results for 0.08 p.u. load reduction scenario in bus-860 in presence and absence of management input [Color figure can be viewed at wileyonlinelibrary.com]

Compared to previous conditions, frequency fluctuations are higher in this case, though the proposed control approach is capable of low-frequency controller (LFC) correctly. Also, the amount of production of each unit of DG is expressed. In this case, the power generated by the turbine is about 0.1 p. u. and the rest of the power is produced via other DGs. Table 6 lists production costs and states that network control is more appropriate than unmanaged control.

Generally, four test cases were investigated, and the first one included two subsets. The cost of producing each test case with the presence of the MIMO controller is shown in Figure 15. The cost of each case has decreased about 22.94%, 23.19%, 28.86%, 0%, and 29.75%, respectively. The advantages of the MIMO controller, in addition to controlling the cost of producing power, can be seen in the effective control of frequency.

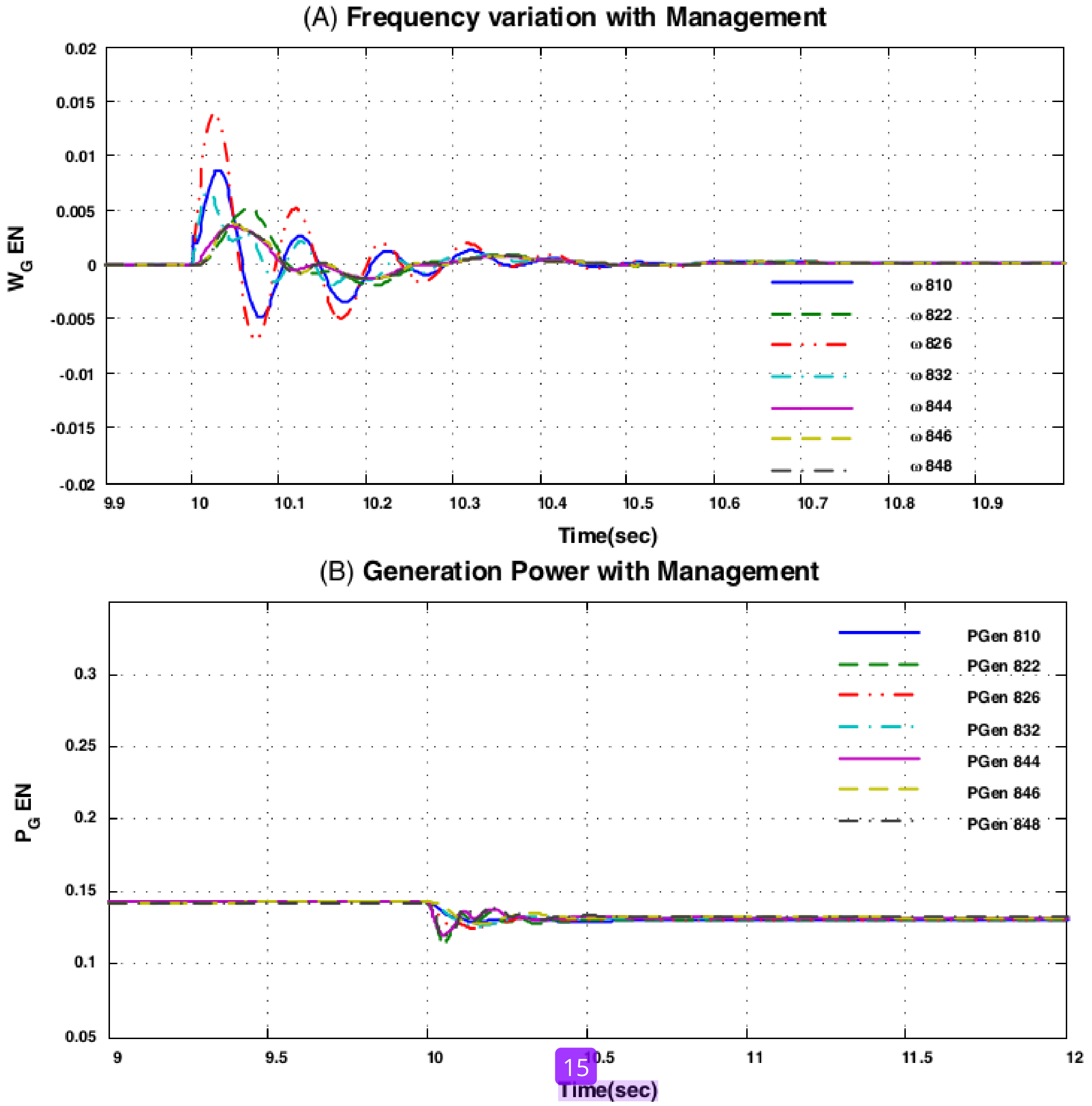

FIGURE 13 Obtained results for 0.08 p.u. load reduction scenario in bus-828 in the same price condition [Color figure can be viewed at wileyonlinelibrary.com]

7 | CONCLUSION

The LFC and power flow management of DGs are the main purposes in the autonomous condition of a micro-grid. The present work proposed a MIMO control system to get LFC and power flow management targets, which integrated their designing process. In most of the related papers, their designs are separately performed, which results in a disruption in the results of both of them. This problem is tackled by the offered controller design method of this paper. Also, this paper utilized the GPSO algorithm for determining the optimal values of the decision variables of the proposed control system that optimized their values in a supervisory manner for all agents of the MAS system. The proposed GPSO improves the balance of seeking ability in various steps. Afterward, the stability of GPSO, as well as synthetic fuzzy + GPSO, was guaranteed with robust

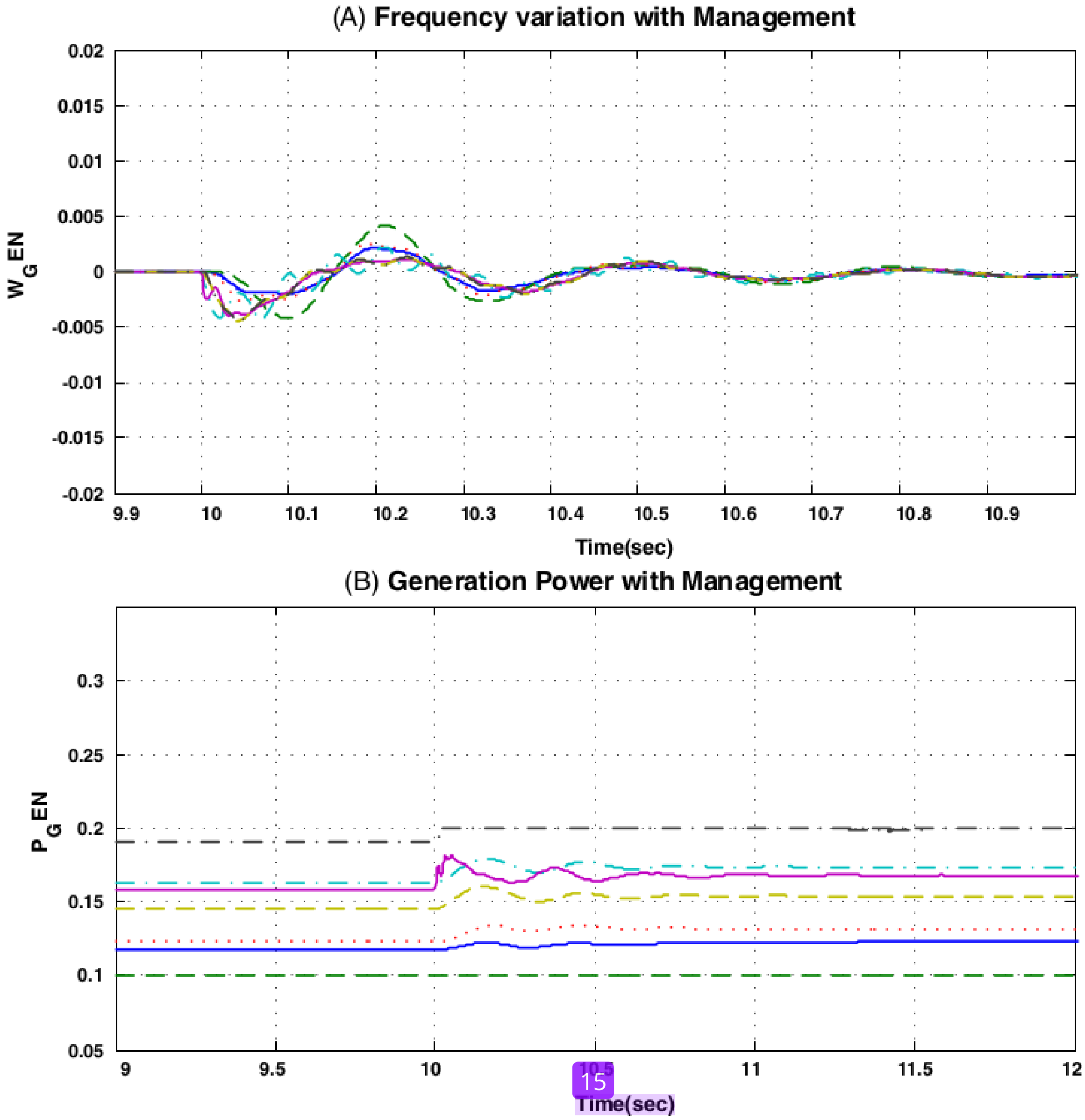

FIGURE 14 Obtained results of 0.05 p.u. load reduction in bus-828 and constraint on a wind turbine in the presence and absence of management input [Color figure can be viewed at wileyonlinelibrary.com]

theory and the Lyapunov approach. To have a rich validation, we considered a network composed of different kinds of DGs covering of wind turbine, PV system, synchronous generators as well as the fuel cell in autonomous condition for evaluation of our proposed control method. Finally, the results were presented for two modes of managed and unmanaged (using MIMO and SISO controller). According to the obtained results, the MIMO controller, besides maximizing the revenue of power production by each agent, can control the frequency oscillation efficiently.

Also, the main contributions of the proposed study can be summarized as follows:

- Designing a multiagent controller based on MIMO fuzzy concept to control DGs in the micro-grid aiming to load frequency control and optimal power management in islanded mode.

TABLE 6 Power production expenditure for 0.05 p.u. load reduction scenario in bus-828 and constraint on a wind turbine in the presence and absence of management input

Parameters	DG810	DG822	DG826	DG832	DG844	DG846	DG848
Power cost ($/kw)	0.0031	0.0026	0.0043	0.0035	0.0034	0.0037	0.0031
Managed produced power	132.64	100	135.94	166.8	161.94	157.24	200
Unmanaged produced power	75.92	28.25	300	116.3	200	147.3	186.78
Power cost of managed mode	281.012		Power cost of unmanaged mode			389.356	

Abbreviation: DG, distributed generation.

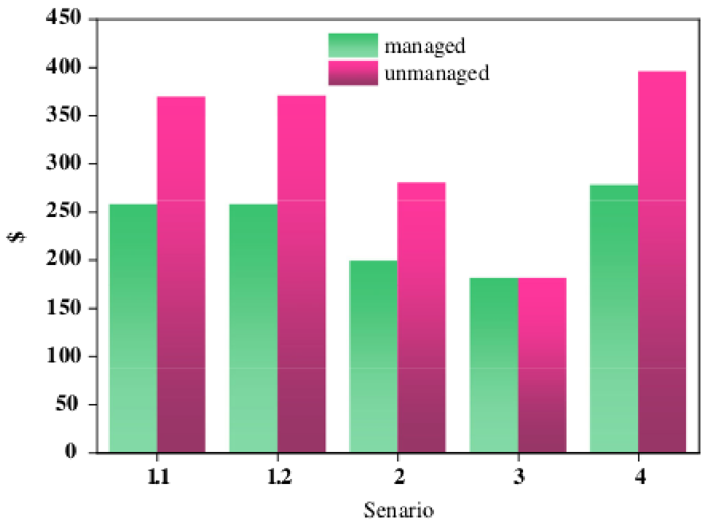

FIGURE 15 Compared results of power production expenditure for multiobjective fuzzy controller optimization method and SISO control systems [Color figure can be viewed at wileyonlinelibrary.com]

- The objective functions in this paper include the cost of generations and load frequency control in micro-grid with island mode.
- An integrated controller is proposed for achieving the stability of the network and optimal management of the system simultaneously.
- Optimization of the studied system by the GPSO method with a stability guarantee.
- Analysis of the stability of the proposed controller alongside the GPSO optimization method.
- Four different scenarios are considered here for more evaluation of the proposed method. The cost of each scenario has decreased by approximately 22.94%, 23.19%, 28.86%, 0 %, and 29.75%, respectively with preserving the stability circumstances.

8 | FUTURE WORKS

The stability analysis is a significant problem in power networks. This paper aimed to guarantee the stability of a novel optimization algorithm and MIMO fuzzy systems. However, the best way to perform such works is to obtain the mathematical model of the grid. Using the mathematical model, the model-based control method can be utilized to design the control system and manage the power-flow. These model-based methods include some significant advantages such as stability guarantee, algorithmic and developable controller design, high accuracy, the high ability for disturbance rejection, and deal with uncertainties.

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APPENDIX A

Parameters of considered DGs in the case study of present work (captured in Figure 1) that are modeled with MATLAB/SIMULINK are listed in the below tables.

TABLE A1 DG2 and DG7 synchronous generator parameters

Parameter	Value	Unit
f	60	Hz
Vt	460	V
SG	200	kW
Pole	2	–
H	0.1753	s
Friction factor	0.01579	p. u.
Xd	2.84	p. u.
X′ d	0.18	p. u.
X″ d	0.13	p. u.
Xq	2.44	p. u.
X″ q	0.36	p. u.
Xl	0.09	p. u.
T′ d	0.08	seconds
T″ d	0.019	seconds
T″ q	0.019	seconds
Rs	0.026	p. u.

TABLE A2 DG4 and DG5 synchronous generator parameters

Parameter	Value	Unit
f	60	Hz
Vt	460	V
SG	300	kW
Pole	2	–
H	0.1986	seconds
Friction factor	0.01777	p. u.
Xd	3.22	p. u.
X′ d	0.21	p. u.
X″ d	0.14	p. u.
Xq	2.79	p. u.
X″ q	0.38	p. u.
Xl	0.09	p. u.
T′ d	0.08	seconds
T″ d	0.019	seconds
T″ q	0.019	seconds
Rs	0.0235	p. u.

TABLE A3 DG6 Wind frame parameters in micro-grid

Parameter	Value	Parameter	Value	Parameter	Value
Jt	25kg/m^2	*PG*	300 kW	ρ	1.31 kg/m^2
Ct	81	ωr	2 rad/s	Γ	37.5
Kt	81	*Tg*	150 kN. m	*R*	28 m

TABLE A4 DG1 VSC-based distributed generation parameters in micro-grid

Parameter	Value	Parameter	Value	Parameter	Value
f	60 Hz	*Rt*	1.5 mΩ	*PG*	100 kW
Vt	380 V	*Lt*	300 μH	DC Voltage	800 V

TABLE A5 DG1 VSC-based distributed generation parameters in micro-grid

Parameter	Value	Parameter	Value	Parameter	Value
f	60 Hz	*Rt*	0.75 mΩ	*PG*	200 kW
Vt	380 V	*Lt*	150 μH	DC Voltage	800 V

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