

Multi-Agent Based Controllers for Distributed Generators

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Abstract— This paper presents a novel multi-agent based control architecture for transient stability enhancement of distribution systems that contain distributed generators. The proposed control architecture is hierarchical with one supervisory agent that optimizes the overall process and a distributed number of local control agents associated with each distributed generator. Control and protection actions need a fast reaction time and are taken by the local control agents. Coordination, learning, modifications of the criteria and parameters for the control and protection equipment, are performed at the global control agent. The proposed control architecture is illustrated to enhance the transient stability of power distribution system with three microturbines as distributed generators.

Index Terms— Multi-Agent system control, Distribution system stability, Distributed generators, Microturbine

I. INTRODUCTION

Traditional electric power systems consist of large, power generating plants interconnected via high-voltage transmission circuits to load serving entities that deliver power to end-users at lower voltages using local distribution networks. However, interest in the use of distributed generators has increased significantly over the past few years because of the potential to increase reliability and lower the cost of power through the use of on-site generation. The initiation of competition in the electric power industry, in which customers have the choice to select their energy providers and to participate in production, has been an incentive for this increased interest. In addition, the development of small, modular generation technologies such as microturbines, photovoltaics, wind turbines, and fuel cells has also contributed to this trend. Distributed generators and storage devices can have many benefits. However, novel operational and control concepts are needed to properly integrate them into the power system. Control strategies must be further developed to achieve the targeted benefits while avoiding negative effects on system reliability and safety. The current power distribution system was not designed to accommodate active generation and storage devices at the distribution level. Compatibility, reliability, power quality, system protection, and many other issues must also be

considered before the benefits of distributed generators can be fully obtained.

Although existing literature addresses the requirements of distributed generators operation and interconnection to the distribution system, the cumulative effect of numerous types of distributed generators on a given feeder is less understood [2]. The extent of the eventual integration of distributed generators into the electrical distribution system will depend on the constraints and standards imposed by the local utility. The impact of connecting small synchronous generators to a nine-bus system has been analyzed in [3] and it was concluded that increasing the perturbation rate tends towards instability. Transient stability characteristics of a distribution system consisting of five distributed generators, which are gas turbine driven synchronous generators of various sizes (5-25 MW), is analyzed in [4]. Simulation results confirm that three phase faults can cause all of the generators to lose synchronism. This situation can even be worse if different distributed generators are used. Stability of the distribution system depends on the type and number of DGs. Instability may occur if the number of distributed generators increases [5]. Machine time constants, size and inertia are important factors that affect system dynamics. Similar results have been achieved in [6] while investigating effects of the number of microturbines on distribution system stability.

Distributed control and Multi-Agent Systems (MAS) have been reported in several power system applications, with some success in several areas like operation, markets, diagnosis and protection. In [14], an MAS is proposed for diagnostic and condition monitoring. The main task of the proposed MAS is integration of alarm interpretation, fault record classification and protection validation into flexible and scalable architecture. A multi-agent approach to decentralized power system restoration for a distribution system network is given in [15]. A multi agent system to control a fossil fuel power unit by synchronizes the slow response of the boiler with faster response of the turbine generator to achieve fast and stable response during load changes and disturbances is proposed in [16]. Another application of MAS in power system transient stability enhancement via turbine fast valving control is proposed in [17]. The proposed scheme mainly consists of a prediction agent that will predict power system instability and a control agent that will initiate turbine fast valving.

This paper describes a novel control architecture based on multi-agent system to resolve the transient stability problem of distribution system resulted from the integration of distributed generators. The paper is organized as follows. The research motivation is given in section II. Section III presents a brief introduction on MAS. The multi-agent control structure is presented in section IV. This section describes the incorporation of the developed MAS control architecture to distributed generators. Then, section V presents the implementation of the proposed control architecture to IEEE 37 node distribution test feeder with three microturbines as distributed generators. The microturbine model has been developed by the authors and presented in [7]. In section VI, two scenarios are being investigated and simulated using Power System Analysis Toolbox [10] to illustrate the effectiveness of the proposed control algorithm. Conclusions are given in section VII of this paper.

II. MOTIVATION

While the penetration of distributed generators in power distribution systems is increased, these devices can be considered as a control path and can be used effectively to enhance the transient stability of distribution systems. Several efforts by many researchers have been published in control design of distributed generators [4], [6] and [8] but most of these controllers are conventional, decentralized and of fixed structure type. In most cases the controllers' parameters are designed by trial and error or tuned by optimization technique using linearized models. Since the distribution system may get vulnerable with the installed distributed generators such conventional fixed structure controllers does not guarantee stable operation of the distributed generators during large and severe disturbances. In most cases distributed generators get disconnected during disturbances [18] as required by IEEE 1547 Standard for interconnection of distributed generators with electric power systems. Based on these issues, it is clear that there is a need to find a novel control algorithm to overcome different tasks and restrictions. Such control architecture must have the following features:

1. Coordinated control among the distributed generators, to avoid contradictive control actions.
2. Adapted controllers, the control actions must adapt to different operating conditions.
3. Self learning ability to end up with a robust and reliable system.
4. Fast control and protection actions to avoid any damage to the distributed generators while keeping them in service.

In this paper a new control algorithm based on multi-agent system that has the desired features is proposed.

III. MULTI-AGENT SYSTEM

An agent is defined as a computer system or software entity that is situated in some environment, perceiving that environment via sensors and acting autonomously in order to meet its design goals [12]. A multi-agent system is a team of

problem solving agents that can react intelligently and flexibly with changing operating conditions and demands from the surrounding processes. The multi-agent system processes an inquiry and generates an output in form of an activity or information. The inquiry is processed autonomously, depending on the process status and the boundary conditions. The agents are trained in a way that their behavior is following a global process goal. On the other hand each agent acts locally based as much as possible on local data, but despite of this, the global target is reached in the sense of an optimal global performance. In addition, the communication between the agents is used to avoid conflict actions. In this paper we will be dealing with multi-agent control systems since both the target definition and the resulting action of the system serve for controlling a process. The main advantage that can be drawn from such architecture is that it is expected to act over longer intervals and especially within broader boundaries, without having to intervene manually. Multi-agent systems are making sense in complex processes, such as power system, which are underlying high and flexible demands. This is closely related to the fact that actions must be taken regardless of little or prior knowledge. Intelligent talents, such as learning from experience, planning of actions or detection and identification of errors, used to be part of the process operator duties, are integrated into the multi-agent system. The advantages are reflected in the avoidance of human operating errors, the enhancement of the reaction rate and performance, and the reduction of the operator's effort [1].

IV. MULTI-AGENT APPROACH IN CONTROL OF DGs

Operation and control of distributed generators (DGs) becomes a major concern as the number of distributed generators increases in electric power distribution systems. The main objective of having distributed generators in distribution systems is to supply on-site power to the load and reduce the dependency on main substation during steady state operation. However these distributed generators may have harmful impacts on the system during large disturbances. It becomes hard and difficult to come up with coordinated controllers for each distributed generator at every operating condition. A distributed generator is considered to be a control point or path that can be used to control and enhance the stability and reliability of electric power distribution systems. In the area of distributed generators, the control process is organized in a multiple parallel but also hierarchical way. Each distributed generator is equipped with one intelligent controller. All agents are interconnected together via the information base to a global agent. A schematic diagram of the proposed multi-agent control architecture is shown in Fig. 1 and has three different layers. The bottom layer represents the physical distribution network with distributed generators. The middle layer presents the control system layer which is basically one controller or more attached to each distributed generator. The top layer is the multi-agent system layer. In this layer there is a local control agent associated to each

distributed generator and a global control agent that supervises and optimizes the overall process. The details of each agent structure and operation algorithm are presented below.

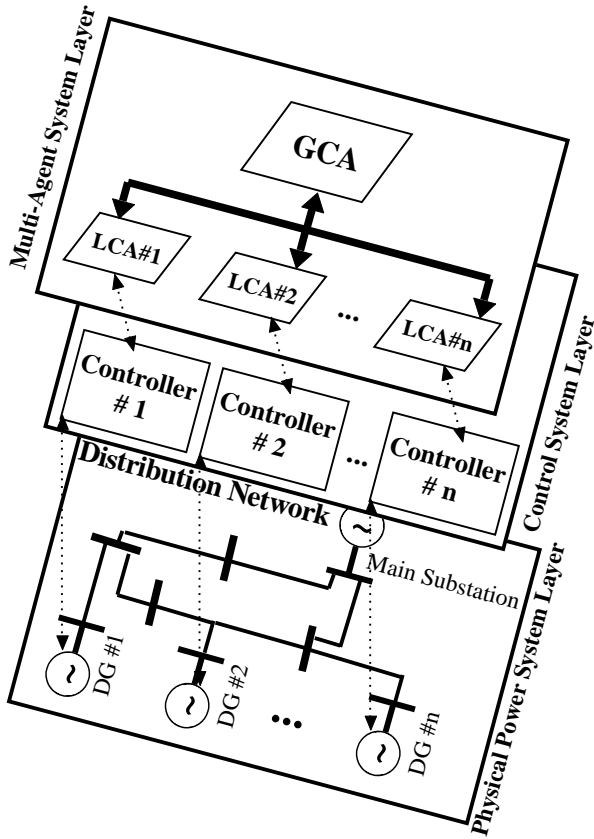


Fig. 1. Multi-Agent based Controllers for Distributed Generators

A. Local Control Agent

A Local Control Agent (LCA) is an agent connected directly to a controller mounted on the distributed generator. It has a direct access to local measurements like information on the distributed generator's bus or distributed generator's operating status. Figure 2 illustrates the function of this agent. The state assessment section continuously evaluates the operating conditions of the distributed generator and compares them with predefined set points. Once a disturbance occurs, the distributed generator operating condition changes and based on that the disturbance can be detected. The execution and adaptation section represents the heart of the agent. It uses the disturbance detection results to execute the control actions. Each LCA is equipped with local data storage. Such feature is extremely useful, especially when the agent loses communication with the rest of the system. The agent will try to map the event with the best suitable controller setting available in the local data storage.

1) Local Control Agent Information Structure

LCA has three types of inputs. The first type is online measurements from the physical layer through sensors as shown in Fig. 2. Some of these measurements are used for system monitoring and assessment to detect any changes or violations in the system, such as terminal voltage of the

distributed generator. On the other hand some of these measurements used by the disturbance detection section as input to Neural Networks (NN) to classify the disturbance and based on that the execution control action and adaptation section generates the proper control action. The second type of input is information from the Global Control Agent (GCA), such as update for data base of a new controller setting or NN update for a new disturbance. This agent generates three types of outputs. The first type is control actions in term of adapting the setting of the controller in the control layer or disconnection of the distributed generator from the grid in case of unsuccessful controllers' settings. The second output is information exchanged with the GCA like passing the Local Emergency Signal (LES) and request for updating the local data base.

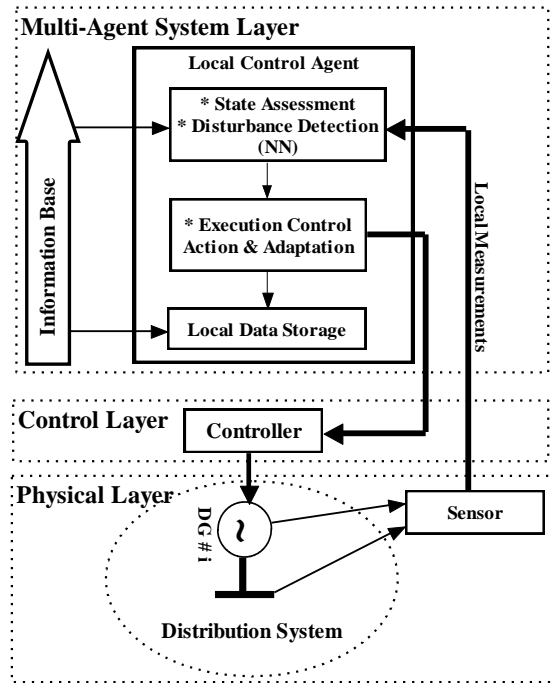


Fig. 2. Local Control Agent

2) Local Control Agent Decision Process

The LCA will follow the algorithm presented in Fig. 3, which has the following steps:

1. The state assessment section continuously evaluates the operating conditions of the distributed generator, such as terminal voltage, shaft speed and generated power. Then it compares them with predefined set points.
2. Once a violation is detected then the disturbance detection section which is equipped with up-to-date trained neural network will identify and classify the detected disturbance and pass the result to execution control action and adaptation section.
3. If the disturbance detection fails, then the collected data is sent to the GCA to update the neural network with the new disturbance.

4. The execution control action and adaptation section will use the disturbance detection section result to assign the proper setting of controller's parameters from the local data base.
5. If the problem is solved, system is stabilized after the disturbance; continue monitoring the system i.e. go to step # 1.
6. If the problem still exists and the violation is driving the system to an instability state, then the execution control action section will disconnect the distributed generator from the grid and continues to supply the local load. The LCA will generate a Local Emergency Signal (LES) and pass it to the GCA.
7. Go back to step # 1.

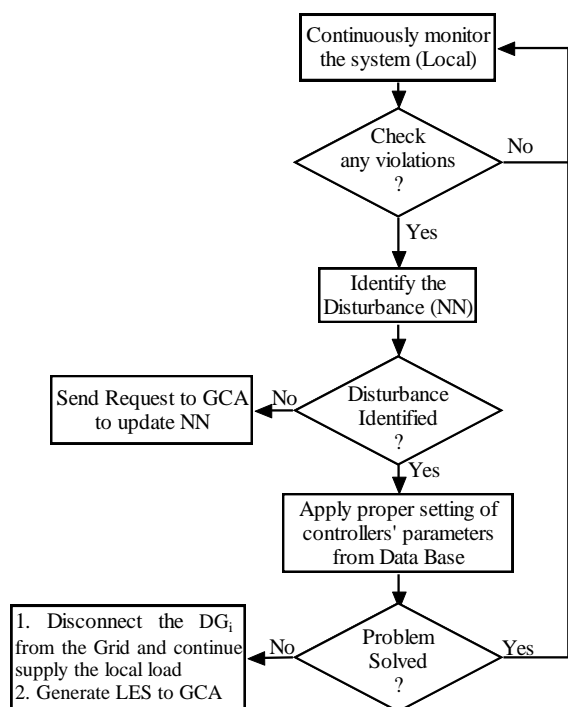


Fig. 3. Local Control Agent Algorithm

3) Local Control Agent Architecture

LCA processes the information measured from the physical layer and accordingly responds with the proper control action. The intelligence of this agent appears in control decisions; the identification of the disturbance according to the local data base by using up to date NN, adaptive control action, and self-learning. This agent adapts the controller's parameters setting to the classified disturbance from the local data base. If the controller setting is unsuccessful a fast control action is passed to the control layer to disconnect the distributed generator from the grid. This action will protect the distributed generator while prevents the propagation of stability problem to the rest of the system. After sending the LES to GCA, the latter will provide the proper controller parameters to that disturbance as well as updating the NN. The LCA can use this particular controller and NN in the future for all similar situations and therefore it has learned and extended the capability of the control layer.

B. Global Control Agent

Fig. 4 illustrates the structure of the Global Control Agent (GCA). It represents the brain of a multi-agent control system. This agent contains three main parts: overall system evaluation and supervision, coordination and learning, and emergency signal section. The main target of the GCA is to keep the system running within the predefined operating conditions, such as known stability margins (voltage stability, synchronization, etc.) during any possible large disturbances. The overall system evaluation and supervision section provides continuous assessment of the system based on LCAs' performance. The emergency section processes the generated LES from LCAs. In addition it is responsible for initiating the Global Emergency Signal (GES). Both cases are reported to coordination and learning section.

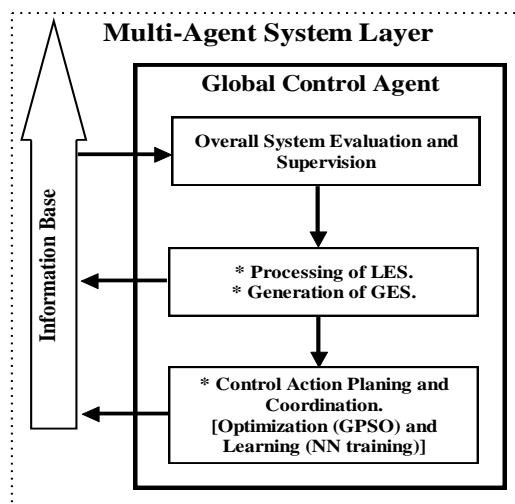


Fig. 4. Global Control Agent

The coordination and learning section is equipped with Guided Particle Optimization technique (GPSO) for controller design and Neural Network (NN) training section to update the LCAs networks with the new reported disturbances. GPSO is a new optimization technique developed by the authors and presented in [8] and [13]. The coordination and learning section process the reported LES or GES and conducts off-line study to design and coordinate new controller's settings to the associated faulted LCAs. In addition it runs NN training to include the new disturbance in the local networks. The designed settings and trained networks will be passed to LCAs via information base and stored in a local data base so that the LCAs can use designs for future similar situations. Therefore it has learned and extended the capability of the LCAs. Then, it will initiate a request to restore the disconnected distributed generators and bring them back to the grid.

1) Global Control Agent Information structure

Unlike the LCA, GCA exchanges information with local control agents only and does not interfere with the other layers. The input to this agent is the local emergency signals from local control agents and requests to update the local control agents' data base with controller's settings or neural networks

updates. The GCA generates output which is either GES or updates to local control agents data base.

2) Global Control Agent Decision Process

The GCA will follow the algorithm presented in the flowchart in Fig. 5; the algorithm can be summarized as follow:

1. The GCA will continuously process the signals and requests from the LCAs in order to update their data bases.
2. Once the GCA receives an LES from any LCA then it conducts a GPSO search to find a new setting for the new disturbance. Then, it will send the new design back to the LCA data base.

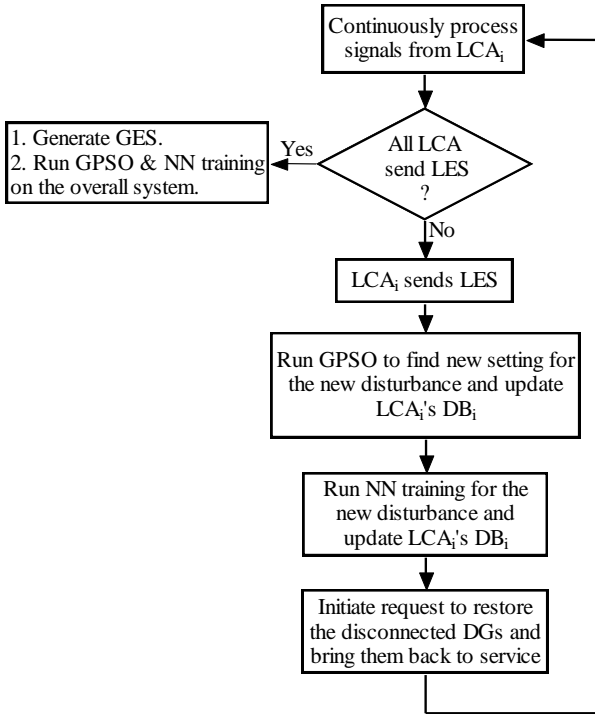


Fig. 5. Global Control Agent Algorithm

3. GCA will also run NN training to update the network with the new disturbance either while receiving LES or individual request. The result will be sent back to LCA.
4. If all LCAs send LESs, then the GCA send a GES to LCA to disconnect all DGs from the grid and supply the remaining loads from the main substation. The GCA will conduct both GPSO search and NN training for the new disturbance, then, send the results back to LCAs.
5. GCA will initiate a request to restore the disconnected DGs and brings them back to service.
6. Go back to step # 1.

3) Global Control Agent Architecture

GCA is responsible for evaluation and supervision of the performance of local control agents by processing the incoming local emergency signals. The most important job of this agent is to perform coordination between the designed controllers at each LCA. This coordination appears in the

optimization process (GPSO) either while processing single LES or during generation of GES. GPSO designs the controller in the first case, while considering the setting of the remaining controllers. In the second case, all the controllers are tuned simultaneously and in a coordinated way. The process of finding the proper controllers' setup and updating the neural networks is a main participation of this agent to the self-learning feature of the MAS based controller.

V. IMPLEMENTATION

The IEEE 37 node distribution test feeder with three microturbines as distributed generators is selected to implement the proposed MAS control algorithm. The average balanced single-phase IEEE 37 nodes system is obtained from unbalanced three-phase system [8]. As shown in Fig. 7, the microturbines rated 160 kW are connected to buses # 5, # 12 and # 36 respectively. The total loading of this feeder is 819 kW. The microturbines provide up to 58% of the total load. They are equipped with Power System Stabilizer (PSS) [8]. If a large disturbance takes the system far away from the operating condition used to tune the controllers, this could have a negative impact and would be no longer effective or even harmful. However, with the proposed MAS based controller such an issue is no longer a problem. The objective here is to use the MAS based control algorithm to enhance the transient stability of the distribution network.

A. Microturbine's Controller.

Microturbine can be controlled via two paths, mainly the mechanical power from the turbine to generator and microturbine's terminal voltage via excitation system, Power System Stabilizer (PSS), see Fig. 6.

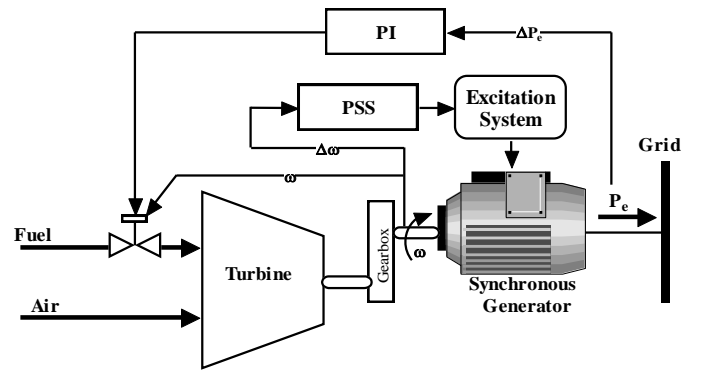


Fig. 6. Microturbine's Control-Loops

The mechanical power controllers are used to match the generated electric power with the load. If a fast disturbance occurred such as short circuit fault, the mechanical power control will be slow and will not be effective. On the other hand, fast action can be taken with a proper excitation control design. The PSS controller is of a fixed-structure type that consists of a stabilizing gain, washout stage and three lead-lag stages as shown in Equation (1).

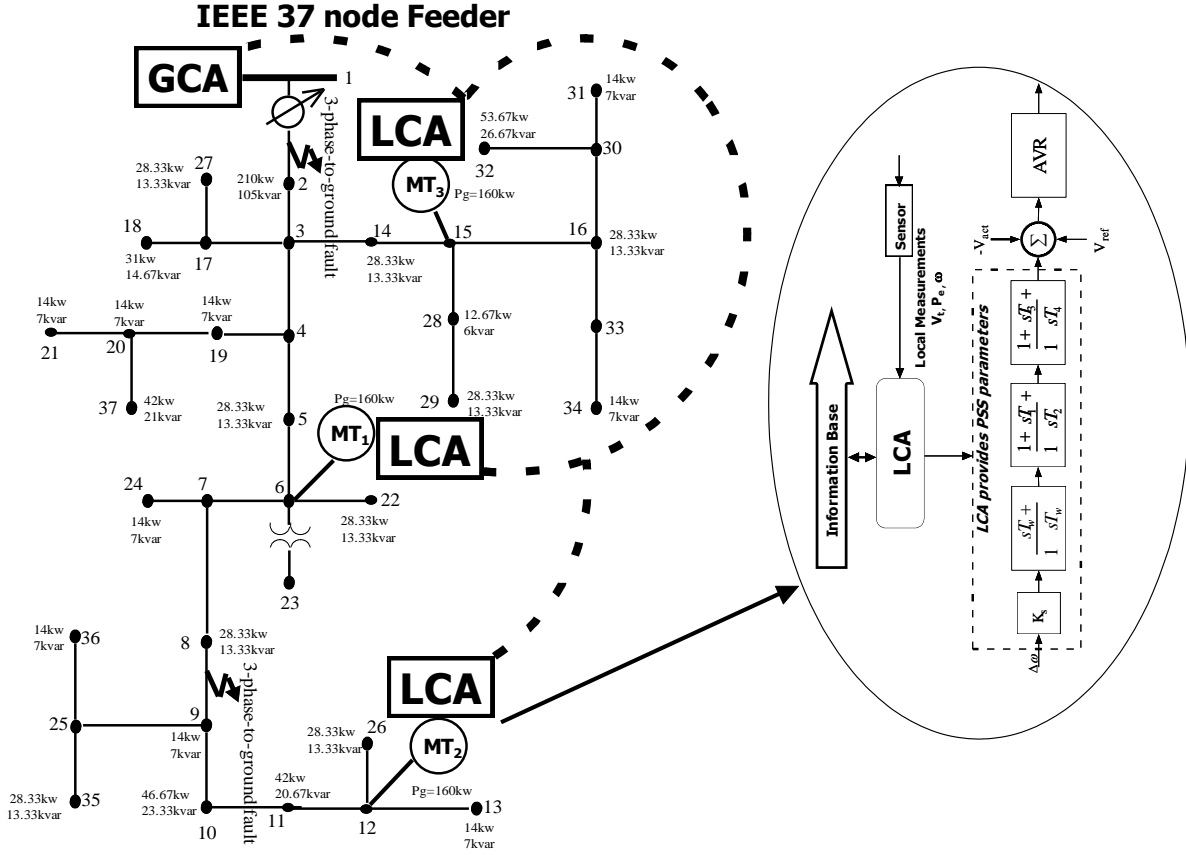


Fig. 7. MAS Based Controller for IEEE 37 Node Feeder with Three Microturbines

$$U = K_s \frac{sT_w}{1 + sT_w} \frac{1 + sT_1}{1 + sT_2} \frac{1 + sT_3}{1 + sT_4} \quad (1)$$

A. Guided Particle Swarm Optimization Setting.

The coordination and learning section in the GCA is equipped with Guided Particle Swarm Optimization [13] to tune microturbine's controller. Table 1 presents the PSO parameters. During the search procedures, GPSO constraint in this case are the microturbine's speed deviations, $\Delta\omega$, and rotor angle, δ .

Equation (3) presents the optimization performance index used in this study.

TABLE 1
PARTICLE SWARM OPTIMIZATION TECHNIQUE PARAMETERS

Bounds	K_s min	K_s max	γ_{min}	γ_{max}	σ_{min}	σ_{max}
		0	400	0.1	10	1
Weighting factors				C_1	C_2	
				2	2.01	
Number of population					50	
Maximum # of unchanged solution					10	
Maximum # of iterations					50	

The dynamics of the overall system can be expressed by a set of nonlinear differential equations of the following form:

$$\begin{aligned} \dot{x}(t) &= f(x(t), u_i(K_j)) \\ i &= 1, \dots, n \\ j &= 1, \dots, m \end{aligned} \quad (2)$$

The equations are simulated using PAT. The objective is for each controller to minimize:

$$\min J_i = \int_0^t (\alpha |\Delta\omega_i| + \beta |\Delta\delta_i|) dt$$

Subject to

Control Constraints:

$$K_{j_{min}} \leq K_j \leq K_{j_{max}}$$

Variables Constraints:

$$\Delta\omega_{i_{min}} \leq |\Delta\omega_i| \leq \Delta\omega_{i_{max}} \quad (3)$$

$$\delta_{i_{min}} \leq \delta_i \leq \delta_{i_{max}}$$

$$V_{ti_{min}} \leq V_{ti} \leq V_{ti_{max}}$$

Where,

x : state variables that includes $\Delta\omega_i$ and $\Delta\delta_i$

ω , δ , and V_{ti} : Generator's speed, power angle and terminal voltage respectively

n : number of controllers "populations or particles"

m : number of parameters to be found "controller's parameters of i -th controller"

K_j : the controller's parameters K_s , T_w , T_1 , T_2 , T_3 , and T_4

B. Neural Network Setting.

The MATLAB Neural Network toolbox is used in this analysis as a part of the GCA coordination and learning NN training section to update the LCAs networks with any new reported disturbances. The following MATLAB functions are used for this purpose:

newff: to create a feed-forward backpropagation network.
train: to train a neural network.

Table 2 presents the NN training section parameters. A MATLAB m-file is written to collect training data from PAT simulations for all possible three-phase-to-ground fault locations in the test system. The voltage magnitude at microturbine's terminal is selected to be the collected training data. The trained network has been tested and proved the ability to classify all possible faults and map them with proper setting of microturbine's controller.

TABLE 2
 NN BACKPROPAGATION TRAINING PARAMETERS

Backpropagation network description	Parameters
Training performance function	sse (Sum-Squared Error)
Training parameter goal	0.1
# of hidden layers	3
# of neurons in hidden layers	[200 300 200]
# of neurons in output layer	22
Transfer function	logsig (in all layers)
training function	traind
Maximum number of epochs to train	100000
Momentum constant	0.95
Minimum performance gradient	1e-10

VI. CASE STUDY

Two scenarios are given below to demonstrate the effectiveness of the proposed MAS control algorithm using the IEEE 37 node feeder as shown in Fig. 11.

A. Case 1, Fault near bus # 1:

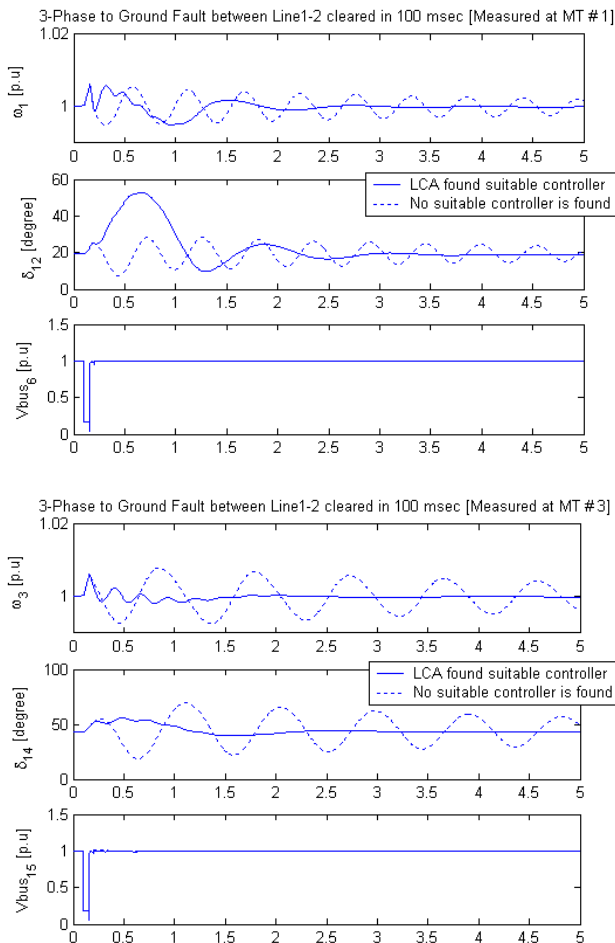


Fig. 8. Three-Phase to Ground Fault Close at bus # 1

In the first scenario: three phase-to-ground fault occurs near bus # 1, close to main substation, at $t = 0.1$ sec and is cleared at $t = 0.20$ sec. The second scenario: three phase-to-ground fault occurs near bus # 8, close to DGs, at $t = 0.1$ sec and is cleared at $t = 0.20$ sec. The proposed control algorithm is implemented and nonlinear simulations are performed for the following cases:

- Disturbance occurred and there is no suitable controller available in the data base for both microturbines. LCAs disconnect the microturbines and send a LES to GCA, which generate or design controllers for this specific disturbance and update the LCAs NN. [No suitable controller is found].
- Disturbance occurred, classified by NN and LCAs adapted the controller to cope the disturbance [LCA found suitable controller].

B. Case 1, Fault near bus # 8:

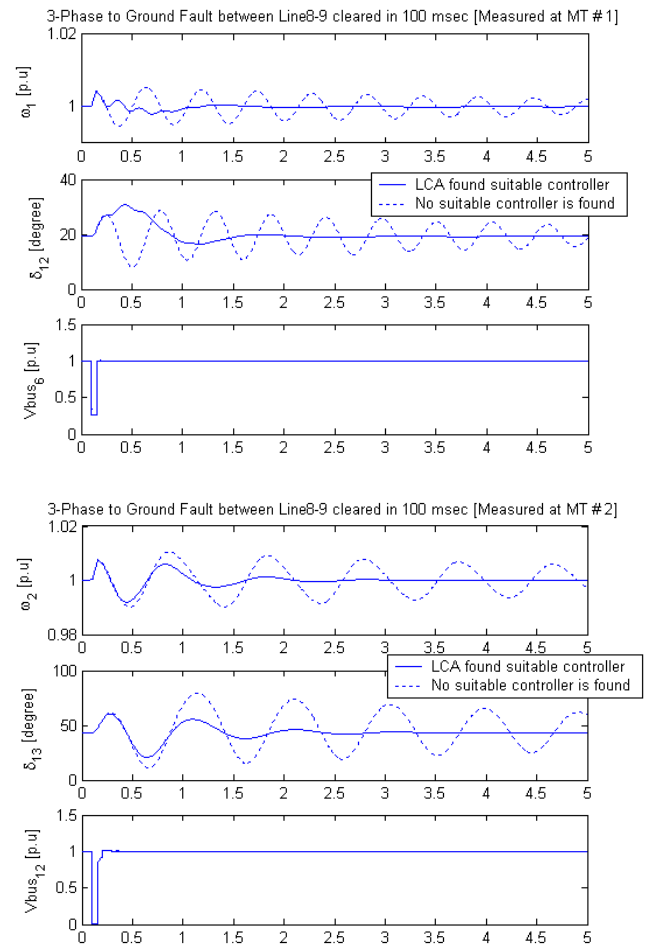


Fig. 8. Three-Phase to Ground Fault Close at bus # 8

From the simulation results, it is clear that the proposed controller extends the operation range of the conventional distributed generator controller. It was impossible to tolerate such disturbances without adapting the setting of the controller. The amount of load and distance between the disturbance and DGs are the main factors to be considered during the design stage.

VII. CONCLUSION

This paper presents an implementation of intelligent control agent approach as a novel control algorithm for distributed generators. The control approach has distributed local control agents and a global control agent. The functions and integration of both types of agents have been explained. Each LCA will try to keep its distributed generator in service (local goal) according to local operation restrictions. It will also try to regulate the overall system (global goal) according to given set-points, which are stored locally in the data base. If a particular agent fails to satisfy the local goal, the associated distributed generator gets disconnected from the grid and continuously supply the local load and LES will be initiated and sent to the GCA. The remaining agents will try to adapt themselves to the new situation. The GCA will conduct an off-line GPSO search to design new controller settings as well as NN training considering the failure situation and will pass them to the information base. Then, a restoration of the disconnected distributed generator will be processed (self-healing). If the global goal is violated then a global emergency signal will be initiated. All distributed generators get disconnected from the grid while loads will have the main substation as the sole source of power. Again the GCA will conduct an off-line learning optimization and training. The system is ready either for manual or automated DG restoration. The IEEE 37 node distribution feeder with three microturbines as distributed generator has been used to illustrate the proposed method. The simulation results demonstrate the effectiveness of the proposed algorithm; system stability is achieved for all the tested cases.

The above summary describes the implementation of multi-agent approach to control of distributed generators. The algorithm can be applied regardless of the number or type of distributed generators. It has the ability of self-learning, so after adequate training, the system should reach a high level of robustness. The MAS based control architecture while extending the controllers' range of operation is still keeping the basic conventional control structure. Another advantage of this approach is that it is not unique and accepts adds-on tasks. Depending on system complexity, other features may be added.

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VIII. BIOGRAPHY

Amer Al-Hinai received his M.Sc. and Ph.D in Electrical Engineering from West Virginia University, Morgantown, USA. Currently, he is an Assistant Professor in the Electrical & Computer Engineering Department at Sultan Qaboos University. His areas of interest are Power Systems: Control and Operation, Multi-Agent Systems: Application to Control of Power Systems, Optimization Techniques and Applications to Power Systems. He carried out more than 20 research projects related to electrical power systems and published over 30 research papers in international journals and conferences.

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