Consensus-Based Demand-Side Participation in Smart Microgrid Emergency Operation

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Abstract—**Recent research works have demonstrated that providing ancillary services for future microgrids is a challenging task due to the lack of sufficient spinning reserves and high cost of storage devices. Therefore, an increasing attention has been given to demand response (DR) as an emerging source to provide the required reserve, especially in emergency operation of the system. This paper proposes a decentralized multi-agent based DR strategy to control the domestic demands during the emergency operation of the microgrid (MG). According to the proposed multi-agent based DR strategy, the domestic loads are grouped based on a predefined priority and are assigned to specific load agents. To implement the information sharing process among the load agents, the consensus strategy is used. Communications among the load agents as a challenging issue of multi-agent systems (MAS) is considered and the effect of communication time delay is investigated. Simulation studies have been carried out on the CIGRE benchmark microgrid with various microsources and domestic loads, showing the effectiveness of the proposed decentralized control scheme.**

Keywords—Consensus strategy, demand response, frequency control, microgrid, multi-agent system.

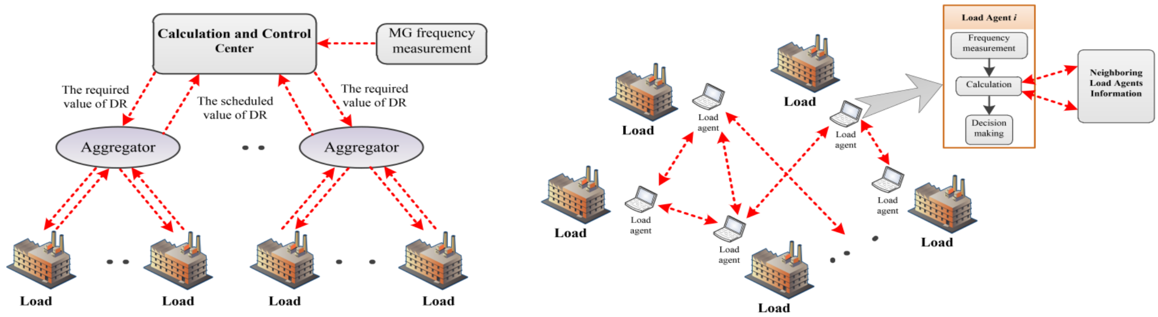
I. INTRODUCTION

The environmental issues lead to increasing concentrations on distributed generation based on renewables. The integration of distributed generation (DG) with a cluster of loads in the power system is related to the novel concept of microgrids (MGs) [1]. The islanded microgrids in comparison with the conventional power systems are weaker grids and have a smaller equivalent inertia. This reality makes islanded MGs sensitive to the system disturbances and vulnerable to frequency deviation, especially when the penetration of intermittent renewable generation is high [2]. As a result, the MGs frequency is exposed to the fluctuations and may change rapidly and even experience a blackout unless there is a sufficient amount of spinning reserve to balance the generation and demand.

To overcome this drawback, the local control of energy storage systems (ESSs) (e.g. batteries, flywheels and ultra-capacitors) was considered as a solution for stabilize the islanded microgrid frequency. ESSs can provide primary frequency support either by injecting power to the grid or absorbing power from it [4]. Energy storage devices are used to improve the performance and stability of the power system [5]. However, because of the low efficiency and the high operational cost of the storage devises along with the high operational cost of generation-side controllers, demand response (DR) can be taken into account as a proper solution to enhance the power system security and reliability [6], [7].

Complementary control of the demands can considerably help in maintaining the grid frequency. It is estimated that in the U.S. about 20% of the loads comes from heating and cooling appliances which could make an effective participation in frequency control during the emergency and normal operation [8]. The contribution of DR to frequency control of the MGs with microgrid central control (MGCC) has been studied in [9]–[12]. In [9], a central demand response strategy is proposed for the primary frequency control of the MG. This method defines three control modes based on the MG frequency behavior following an unplanned event. Based on the frequency deviation, the control center determines the amount of load to be disconnected/reconnected and sends a command to the local load controllers. In [10], according to the local frequency measurement, an emergency demand response is proposed to improve the MG frequency response. In the proposed control strategy, the MGCC is responsible for defining the most adequate technical online solution for managing the demand response following a disturbance. Centralized control systems require a powerful MGCC [13], [14] which is costly and easily suffer from single-point-failure. Furthermore, centralized schemes don't meet the plug and play requirements of the MG and they are not adaptive to the changes of the power network structure. To avoid these shortcomings, decentralized control scheme are introduced. Multi-agent system (MAS) is one of the most popular decentralized control solutions. A MAS has the advantage of surviving to a single-point-failure, and it can carry out a decentralized data processing which, in turn, leads to distribution of tasks and faster decision-making process [15].

This paper introduces a decentralized scheme based on MAS to control the DR participation in MG emergency operation without any requirement to the MGCC. In the proposed scheme, the responsive loads are assigned to specific load agents. The load agents just know their own local information and only communicate with their neighboring agents to share the local information and access the required global information. To implement the information sharing process, the consensus strategy is used. After completing the information sharing process, based on the discovered information, all load agents take a common decision for participation in the MG frequency control.



(a) (b)

Fig. 1. Conceptual scheduling of DR strategies in MG, a) centralized DR strategy b) proposed decentralized DR strategy.

The effect of communication time delay has been tested for the proposed method. The CIGRE benchmark microgrid model, which is developed in *Matlab/Simulink /SimpowerSystems* environment, is used to verify the effectiveness of the proposed method.

II. BACKGROUND

A. *Demand Response Participation in MG Frequency Control*

Demand response can be considered as an economical and effective solution for frequency regulation especially in a smart grid environment where a two-way communication is a necessary requirement. DR mainly consists of two main categories including incentive-based programs (IBPs) and price-based programs (PBPs) [16]. In price-based DR, clients change their consumption based on different electricity prices determined by the electric utility. This approach is out of the scope of this study. In incentive-based DR, users in response to incentive payments presented by utility change their consumption. These programs can be categorized into four groups including: i) Emergency demand response, ii) Demand bidding and buyback, iii) Curtailable/interruptible load; and iv) Direct load control.

The approach proposed in this paper is conceived to be adopted in an emergency demand response program which is commonly contract-based and voluntary [17] and can be also useful in contingencies. In this type of program, if a contingency occurs the system operator sends an emergency message from the control center to all clients that take part to this program [18].

Fig. 1-a shows the conceptual central control for incentive-based DR management in MGs. Any DR scheduling process starts from the control center which determines and requests the desired volume of DR at any given time. Implementing such a DR strategy requires two-way communication links between the aggregators and control center and also between the loads and aggregator. This structure easily suffers from a single-point-failure. For instance, in the case of a communication failure between the control center and an aggregator in any given time, the loads corresponding to that aggregator cannot participate in the frequency regulation. This shortcoming is the same in the case of a communication failure between a load and its corresponding aggregator. Another disadvantage of centralized DR control is a need for a powerful control center to handle a huge amount of data.

Fig. 1-b shows the concept of proposed decentralized multi-agent-based DR control strategy. In this scheme, the controllable loads are assigned to the specific load agents. Each load agent has some local information without having any direct access to the global information of the system. A load agent is just able to communicate with its neighbors to share its local information. By using a proper communication law, the load agents are able to share the information and access the global information and accordingly take a common decision for participation in the frequency regulation of the MG. The information sharing process among the load agents is explained in the following subsection.

B. *Information Sharing With Consensus Strategy*

Multi-agent systems require the information sharing among the agents. The communication among the agents can be accomplished by using the average consensus algorithm. Let $U=(N,E)$ be a network with N agents and E communication lines (two-way). Consider in agent set $N=\{1,2,...,n\}$ each communication line $\{i,j\}\in E$ is an unordered pair of distinct agents. Let r_i^0 be a real number associated to agent i at time t=0. The average consensus problem is to determine iteratively the average $(1/n)\sum_{i=1}^{n} r_i^0$ in a distributed manner at every agent. The following iterative law which is known as average consensus algorithm, is proposed to solve the distributed averaging problem [19]:

$$r_i^{k+1} = r_i^k + \sum_{j\in N_i} s_{ij}(r_j^k - r_i^k), \tag{1}$$

where *i=1,2,...,n; n* is the number of agents; r_i^k, r_i^{k+1} are the real numbers associated to agent i at iteration k and $k+1$ respectively, s_{ij} is the weight coefficient that ensures the communication between neighboring agents i and j. If agents i and j are connected together, $0 < s_{ij} < 1$, otherwise $s_{ij} = 0$. N_i is the index of nodes which are connected to node i.

By considering $\mathbf{R}^k = [r_1^k,...,r_i^k,...,r_n^k]^T$, equation (1) can be written in the matrix form:

$$\mathbf{R}_i^{k+1} = \mathbf{R}_i^k + \mathbf{A}\mathbf{R}_i^k = (\mathbf{I}+\mathbf{A})\ \mathbf{R}_i^k \rightarrow \mathbf{R}_i^{k+1} = \mathbf{D}\mathbf{R}_i^k, \tag{2}$$

where **I** is the identity matrix, and

$$\mathbf{D} = \begin{bmatrix} 1-\sum_{j\in N_1} s_{1j} & \cdots & s_{1i} & \cdots & s_{1n} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ s_{i1} & \cdots & 1-\sum_{j\in N_i} s_{ij} & \cdots & s_{in} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ s_{n1} & \cdots & s_{ni} & \cdots & 1-\sum_{j\in N_n} s_{nj} \end{bmatrix}_{n\times n}. \tag{3}$$

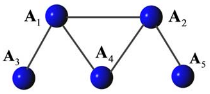


Fig. 2. A typical studied network.

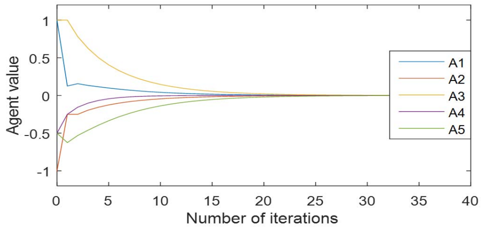


Fig. 3. Consensus-based information sharing.

The square matrix $\mathbf{D}$ is *doubly stochastic* if the sums of each row and each column are equal to ones and its elements are non-negative, i.e., with $\mathbf{V}_{1\times n}=[1,1,...,1]$, $\mathbf{V}\times\mathbf{D}=\mathbf{V}$ and $\mathbf{V}\times\mathbf{D}^T=\mathbf{V}$ [20]. The eigenvalues of $\mathbf{D}$, based on the Gerschgorin's Disks theorem, are lower than or equal to one. Based on the *Perron Frobenius Lemma* [21]:

$$\lim_{k\to\infty}\mathbf{D}^k=\frac{\mathbf{V}^T\times\mathbf{V}}{n}, \tag{4}$$

where, n is the dimension of matrix $\mathbf{D}$. By combining (2) and (4) we can write:

$$\lim_{k\to\infty}\mathbf{R}_i^k=\frac{\mathbf{V}^T\times\mathbf{V}}{n}\mathbf{R}_i^0. \tag{5}$$

From (5), it can be seen that the system reaches to consensus when k approaches infinity. The design of $\mathbf{D}$ determines the speed of convergence. In practical issues, the exact equilibrium is not needed and the number of steps required to converge is nearly equal to:

$$k=\frac{-1}{\log_e(\frac{1}{\lambda_2})}, \tag{6}$$

where λ_2 is the second biggest $\mathbf{D}$ eigenvalue of $\mathbf{D}$ and e is the error tolerance [19]. Generally, for online applications, the weight coefficients are specified by using the *Metropolis* method that is presented in [22]. This method suggests the coefficients that are calculated as follows:

$$s_{ij}=\begin{cases}1/(Max\,(n_i,n_j)+1) & j\in N_i\\ 1-\sum_{j\in N_i}1/(Max\,(n_i,n_j)+1) & i=j\\ 0 & otherwise\end{cases}, \tag{7}$$

where n_i and n_j are the numbers of agents in the neighborhood of the agent i and j, respectively. It is can be shown that the metropolis methods guarantee the necessary conditions to apply the *Perron Frobenius Lemma* to $\mathbf{D}$ (i.e., the sums of each row and column of the $\mathbf{D}$ are ones, and all its eigenvalues are equal or lower than one) in order to achieve the convergence. By defining a positive definite Lyapunov function obtained from first order approximations the stability of algorithm is guaranteed. Interested readers can find more detail on this algorithm in [14]. To show the performance of consensus strategy, let consider the network depicted in Fig. 2. Now, the initial values assigned to each agent are defined:

$$r_1^0=1,\; r_2^0=-1,\; r_3^0=1,\; r_4^0=-0.5,\; r_5^0=-0.5 \tag{8}$$

The equilibrium point for infinite iterations will be

$$r_1^\infty=r_2^\infty=r_3^\infty=r_4^\infty=r_5^\infty=\frac{1}{5}\sum_{i=1}^{5}r_i^0=0. \tag{9}$$

It means that after using the consensus strategy, the number '0' exists in each agent. Fig. 3 indicates the value of each agent for 40 iterations. The agents reach the equilibrium point with 25 iterations considering 0.01 error tolerances.

C. Characterization of the considered MG

Fig. 4 shows the single-line diagram of the CIGRE benchmark microgrid [23] which is used for the simulation of the proposed decentralized multi-agent-based DR strategy. The CIGRE benchmark comprises an LV feeder, both controllable and uncontrollable loads, microsources (such as microturbines, photovoltaic (PV) systems, wind energy conversion systems (WECSs), fuel cells (FCs), and storage devices (like battery energy storage systems (BESSs) and flywheels). The detailed model of thee microgrid components can be found in [24]. The CIGRE benchmark microgrid supplies residential customers. Residential loads usually consist of resistive loads, such as lighting loads, electrical heating and cooking appliances, small induction motors and thermostat-control loads. Thermostatically controlled loads, such as air conditioners, refrigerators, freezers and electric space heaters, are constantly connected to the grid. These types of loads switch between off and on states to maintain the related temperature inside the desired range. However, because of their thermal inertia, these loads can be disconnected for a few minutes without any harm to the consumers comfort [25].

In [26], several home appliances have been grouped, according to Table I, considering the maximum disconnection time for the appliances without leading to consumers discomfort. Group I consists of thermostatically controlled loads which have the longest maximum off time. Group II consists of wet appliances which have induction motors and heaters. Group III and IV consist of the devices with resistive heating elements. Group V consists of lighting loads.

According to Fig.2, it is assumed that in the CIGRE benchmark microgrid each residential customer and apartment building is assigned to a specific load agent. Each load agent has the local aggregated information of the corresponding apartment or residential customer without any direct access to the global information of the system.

III. DECENTRALIZED MULTI-AGENT BASED STRATEGY FOR PARTICIPATION OF DR IN MG FREQUENCY CONTROL

We propose a decentralized multi-agent based strategy for participation of DR in the MG frequency control which depends on the MG frequency deviation. It is assumed that in the CIGRE benchmark microgrid each residential customer and apartment building is assigned to a specific load agent. Each load agent has the local information available power of each load group corresponding to an apartment or residential customer. When a disturbance occurs in the MG, if frequency deviation Δf passes the predefined threshold, the load agents start sharing their local information about the available power of each load group.

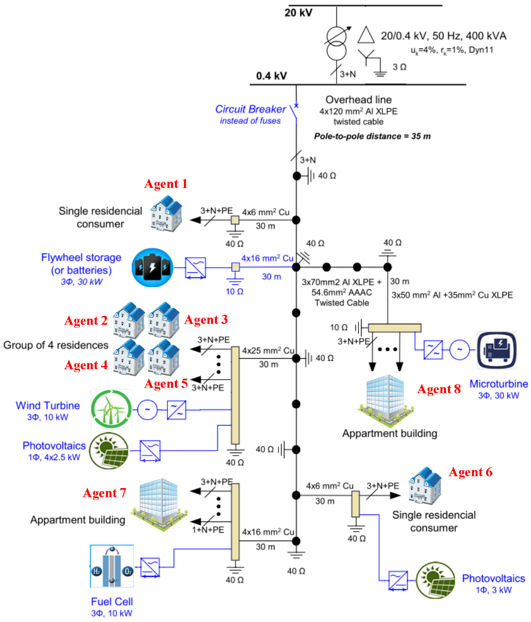


Fig. 4. CIGRE benchmark microgrid.

TABLE I
SPECIFICATION OF LOAD GROUPS

Group	Appliances	Maximum off time
I	Electric space and water heater, Refrigerators and Freezers	5 min
II	Washing machines, Tumble dryers	3.5 min
III	Cooking appliances	2 min
IV	Electrical in-line heaters	15 s
V	Lighting loads	4 s

A. Information Sharing Process

By using the aforementioned distributed averaging process, each load agent updates its value to a linear combination of its neighbor's value. By considering k load groups participating in frequency control, the point of convergence for each load group is as follows:

$$P_k^{conv.} = \frac{1}{n}\sum_{i=1}^{n} p_{i,k}^{(0)} , \tag{10}$$

where n is number of load agents and $p_{i,k}^{(0)}$ is the initial value of the load agent i correspond to the load group k. By considering time delay to achieve the convergence, the total available power from all load groups is:

$$\begin{cases} P^{TOT} = n \times \sum_{j=1}^{k} P_j^{conv.} \\ T_d = \dfrac{N_{iteration} \times k \times N_b}{C}, \end{cases} \tag{11}$$

where P^{TOT} is the total of each load group, T_d is time delay, $N_{iteration}$ is the number of needed iterations to reach the convergence, N_b is the number of required bits to represent each load agent value, and C is the communication link speed. In [14] it has been shown that the speed of consensus-based information sharing is independent from the initial agent values. Therefore, all load groups achieve to the convergence simultaneously.

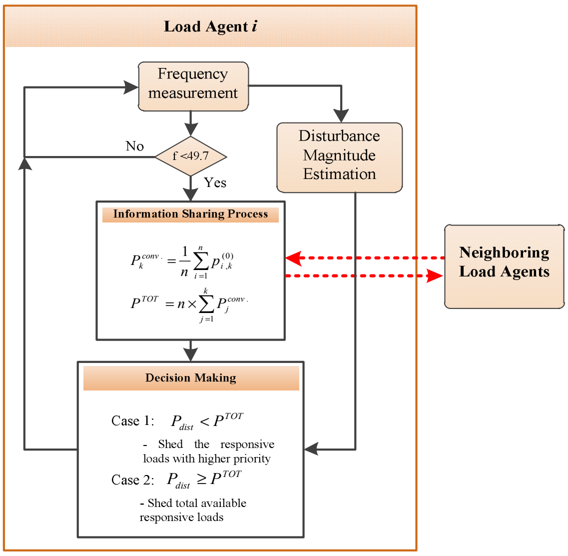


Fig. 5. Function of load agent *i* for participation in MG frequency control.

B. Decision making of the load agents

The function modules of load agent *i* is presented in Fig. 5. Each load agent measures the frequency of the MG. If a disturbance occurs in the MG, first the load agents estimate the size of disturbance. The size of disturbance P_{dist} can be estimated online based on the rate of frequency decline [27]:

$$P_{dist} = 2H \times m_0 \ (pu) \tag{12}$$

where m_0 is the initial slope of the frequency decline and H is the inertia constant. The inertia constant may vary during various operating period. Therefore, to track this value, recursive least square algorithm can be applied to estimate this value in real time [28]. In this paper, we suppose that each load agent is equipped with a disturbance magnitude estimation block to determine the size of disturbance.

As illustrated in Fig.5, if the frequency is lower than 49.7 Hz the load agents start to share the local amount of available power to be shed in each load group. After achieving the convergence, all load agents make a common decision. In the case that $P_{dist} \geq P^{TOT}$, all available responsive loads in each group will be shed. If $P_{dist} < P^{TOT}$, the amount of shed responsive loads is equal to the disturbance based on the priority of the loads. According to Table I, the load group I has the maximum off time. Therefore, the first priority is given to group I. The groups II, III, IV have the next priority, respectively. In order to not disrupting the consumer's comfort, the group V (lighting loads) is not involved in the proposed decentralized multi-agent based DR strategy.

IV. SIMULATION RESULTS AND DISCUSSIONS

In order to verification of the proposed method, it is applied to the CIGRE benchmark microgrid shown in Fig. 2. The CIGRE benchmark microgrid model along with the MAS system are developed in *Matlab/Simulink* environment using *SimPowerSystem* toolbox. A multi-master control approach is adopted in which the inverter of energy storage and microturbine act as voltage source inverter (VSI).

The other inverters are controlled in constant power (PQ) control mode [24]. The nominal voltage of the MG is 0.4 kV and it supplies a total of 8 residential and apartment buildings. For simplicity and without sacrificing generality, it is assumed that each single residential customer consumes 8 kW and each apartment building consumes 21 kW. The total generation power of the microsources is about 60 kW. Therefore, in normal connected operation mode, the upstream network injects about 30 kW power to the MG. To investigate the effectiveness of the proposed multi-agent based emergency control of DR we consider the communication topology of Fig. 6 for the load agents. The two general scenarios are defined and tested as follows:

A. Scenario 1: MG with Sufficient Responsive Load Capacity

In this scenario, it is assumed that the MG has sufficient amount of responsive load to restore the frequency. At the beginning of simulation, the MG is connected to the upstream grid and absorbs about 30 kW power from it. Suddenly the MG is disconnected and operates in islanded mode and the frequency starts to decrease. The load agents continuously measure the MG frequency. When the frequency passes the threshold of 49.7 (Hz), the load agents start to share the information about the amount of available responsive loads in each load group. The amounts of available responsive loads at the moment, corresponding to each load agent in each load group are presented in Table II. It can be seen that the total available reserve of the responsive loads is 32 kW. To share the local information of responsive loads, we consider the topology of Fig. 6. After achieving the convergence, based on the function of load agents (Fig. 5), a common decision is taken and the required amounts of responsive loads (30 kW of the loads with less importance) are shed. It should be noted that for all case studies, the number of required bits to represent each load agent value is equal to 16 bits, and a narrow-band 100 kb/s communication link is used. The total available responsive load for load agent *i* in each iteration can be obtained by the sum of the available power for all four load groups multiplied by *n* as follows:

$$P_i^{TOT}\Big|_{iteration\ \ j} = 8\times(p_{i,1}^{(j)} + p_{i,2}^{(j)} + p_{i,3}^{(j)} + p_{i,4}^{(j)}) \qquad (13)$$

As already mentioned, in order to not disrupt the consumer's comfort, the group V (lighting loads) is not involved in Eq. (13). Fig.7 shows the total available power of responsive loads discovered by the information sharing process using the consensus strategy. By using the consensus strategy, the convergence is achieved in 26 iterations. Therefore when the frequency passes the threshold, according to (11), the time delays to reach the convergence is 0.01664 (s). Fig. 8 shows the frequency of the MG in this case. At t=2 (s), the MG is exposed to an unintentional islanding and the frequency starts to decrease. The figure shows the successful performance of the proposed decentralized scheme.

B. *Scenario 2: MG with Lack of Sufficient Reserve Capacity*

In this scenario, it is assumed that the wind energy conversion system is disconnected from the MG. Therefore, in normal connected operation mode, the upstream network injects about 40 kW power to the MG. Suddenly at t=2 (s) the MG is disconnected and operates in islanded mode and the frequency starts to decrease. The total available reserve of the responsive loads is 32 kW. As a result, the MG has not sufficient amount of responsive load to restore the frequency in islanded mode. When the frequency passes the threshold of 49.7 (Hz), the load agents start to share the information about the amount of available responsive loads in each load group. Similar to the previous scenario, the local information are discovered through 26 iterations and the communication time delay is 0.01664 (s). Because of the lack of the sufficient reserve from the responsive loads, in the decision making function of the load agents, the condition of 'Case 2' is met. Therefore the load agents decide to disconnect all o available responsive loads. Fig. 9 shows the frequency of the MG in this scenario. A proper secondary control scheme is required to eliminate the remained frequency error which is not in the scope of this paper.

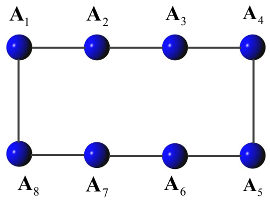


Fig. 6. The way of connection of load agents.

TABLE II
AVAILABLE RESERVE OF RESPONSIVE LOADS

	Available responsive load (kW)				
Load agent	Group 1	Group 2	Group 3	Group 4	Total
A1	2	0	0.9	0	2.9
A2	2	2	0	0	4
A3	2	0	1.5	0.5	4
A4	1.5	0	2	0	3.5
A5	0	1.3	2	0	3.3
A6	0	2	0	0.7	2.7
A7	4	0	0	1.5	5.5
A8	5	0	0	1.1	6.1

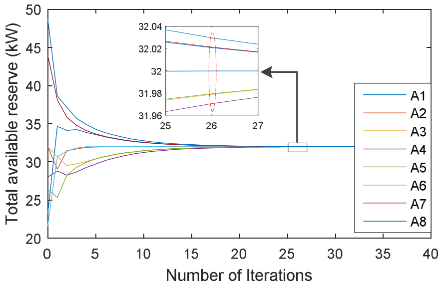


Fig. 7. Total available power of responsive loads.

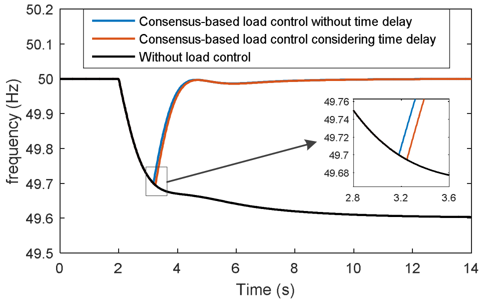


Fig. 8. Frequency response of MG in scenario A.

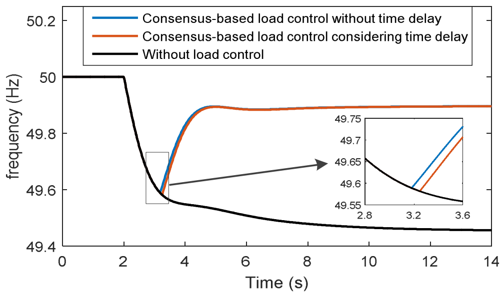


Fig. 9. Frequency response of MG in scenario B.

Results show that the speed of consensus algorithm is enough to be used for the DR control in emergency conditions. Regarding the implementation of communication system, it should be noted that according to cable news network (CNN), the average Wi-Fi speed in the United States (US) is 5 Mbits per second. However, this rate tends to fluctuate. Speeds for 4G vary depending on their carrier. High speed packet access (HSPA+) has a maximum speed of 42Mbps, however worldwide interoperability for microwave access (WiMax) offers speeds up to 75Mbps. The fastest maximum speed belongs to long-term evolution (LTE) which is 300Mbps. Average speeds vary depending on the location of user and even an LTE user can experience speeds as low as 1Mbps. In this paper, the communication link speed is considered to be 100 kb/s. Therefore, considering the required communication speed, both 4G signal and Wi-Fi can be easily used for implementing the proposed method.

V. CONCLUSIONS

This paper developed a new decentralized multi-agent based DR strategy to control domestic demands during the emergency operation of a microgrid. In the proposed decentralized scheme, the domestic loads were grouped and assigned to specific load agents. The consensus strategy was used for sharing the local information among load agents. Based on the global discovered information, the load agents took a common decision for participating in the microgrid frequency control in emergency operation. The effect of the communication time delay effect was also tested for the proposed method. Simulation results proven the effectiveness of the proposed multi-agent based DR control strategy.

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