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ORIGINAL RESEARCH

A multi-agent privacy-preserving energy management framework for renewable networked microgrids

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Abstract

This paper proposes a fully distributed scheme to solve the day-ahead optimal power scheduling of networked microgrids in the presence of different renewable energy resources, such as photovoltaics and wind turbines, considering energy storage systems. The proposed method enables the optimization of the power scheduling problem through local computation of agents in the system and private communication between existing agents, without any centralized scheduling unit. In this paper, a cloud-fog-based framework is also introduced as a fast and economical infrastructure for the proposed distributed method. The suggested optimized energy framework proposes an area to regulate and update policies, detect misbehaving elements, and execute punishments centrally, while the general power scheduling problem is optimized in a distributed manner using the proposed method. The suggested cloud-fog-based method eliminates the need to invest in local databases and computing systems. The proposed scheme is examined on a small-scale microgrid and also a larger test networked microgrid, including 4 microgrids and 15 areas in a 24-h time period, to illustrate the scalability, convergence, and accuracy of the framework. The simulation results substantiate the fast and precise performance of the proposed framework for networked microgrids compared with other existing centralized and distributed methods.

1 | INTRODUCTION

Microgrid (MG) is defined as an aggregation of distributed energy resources (DERs), loads, and energy storage systems (ESSs) connected with each other, which try to meet the power balance by exchanging energy among themselves and with the upstream distribution system (DS) (also called utility or main grid) [1]. Some of the main advantages of MGs can be named as higher reliability, power quality, enhanced voltage profile, lower power losses and costs, fewer interruptions, and better electrical services. The many advantages of single MGs motivated the researchers to introduce an advanced structure for MGs called networked MGs (NMGs) to not only benefit from all advantages of a single MG, but also make use of the pros coming out of this interconnected supporting structure. NMGs are defined as the interconnection of several MGs to each other and to the utility, making it possible for a multi-directional power exchange among themselves and with the DS [2]. Such a supporting structure can yield many overhead benefits, including but not limited to more global power dispatches due to changing from one MG into several interconnected ones, fewer power losses, and a higher load-generation balance in both normal and contingency modes.

While the concept of NMGs can bring many benefits to electric companies and consumers, there are still emerging challenges mainly due to the high complexity of these systems. One of the main challenges is the power exchange among MGs and within the main grid to provide the most appropriate power dispatch with the highest economic revenues. The operation of NMGs can be categorized into three main categories:

1.1 | Centralized methods

The traditional way of achieving optimal operation, which solves the optimization problem in a centralized approach. These methods optimize the problem by centrally calculating after assembling the information of all units in the centre. These methods are the most accurate schemes as they consider the entire system as a whole and can solve complex optimization problems. They have access to all the information in the system, allowing for precise decision-making. On the other hand, computational and communication burdens are the most significant issues of centralized schemes. Moreover, the privacy of the units, the monopoly of the central unit, and single failures are threatening these systems.

1.2 | Decentralized methods

To overcome some of these drawbacks, decentralized methods with the intention of achieving a global solution by performing local calculations are introduced. Decentralized methods usually split the computation operations among several units (MG operators), and these units exchange their information (e.g. price and power flow) with the overhead coordinator (main grid) to meet the total power demand. These parallel computations can help centralized methods to be scalable. In addition to local convergence, several exchanges between each MG and the upstream unit are required to reach the global solution, which enables the global resource allocation deviating from the optimal point. However, these hierarchical communications may result in the slow performance of these methods due to the bi-levelled nature of the presented methods. Moreover, the privacy of the local units is not preserved against the upper layer [3].

1.3 | Distributed methods

Distributed methods are developed in order to get to the optimal operating point by exchanging information among the agents using local computations [4]. In other words, a distributed system is controlled by several interconnected intelligent agents that exchange information with each other. Each agent in the distributed system shares its current status with other connected (neighbouring) agents and simultaneously updates its own status based on the information received from its neighbouring agents. Then, after several iterations, the desired/optimal statuses are calculated. Distributed approaches can resolve the issues that arise from centralized and decentralized methods. They eliminate the need for a central party to assemble data and control the system. Thus, the burden of central control and management, which was on the central calculation unit in centralized methods, is shared among different agents. This can facilitate the control process, enhance the speed of calculation, and solve the single point of failure and the monopoly of the solitary controller over the system. Moreover, the information privacy of the units is preserved against the upper layer/unit.

Despite these benefits, distributed methods confront some challenges:

- Agents must share information with other agents, which may compromise their privacy against their peers [5].
- Some distributed methods require a leader, which can cause privacy issues or make the method sensitive to single-point failures.
- Each agent in the distributed system requires a local calculation and storage space, which may entail significant investment for grid owners and entities.
- Distributed systems must have an area for updating rules among agents and enforcing punishment for delinquent agents in the system.
- The saddle point of some distributed methods may not always reach the optimal solution. The classification of the abovementioned methods for operating NMGs and a simple illustration of the three types of methods are presented in Figure 1.

In general, contemporary distributed optimization methods in the field of power scheduling for smart grids and microgrids are categorized into three main classes: 1) weighted-averaging-based approaches [6] 2) primal-dual Lagrangian-based methods [7] 3) methods based on the alternating-direction method of multipliers (ADMM) [8]. However, the first class requires improvements in many cases [9] to deal with complex problems, and there is not a general and proper formation suitable for all problems. For instance, in the case of economic dispatch and energy management, quadratic cost functions in their simple format may not be sufficient. Additionally, a leader or coordinator is needed in many cases, such as ref. [6], to achieve consensus among the agents, which is considered a downside for distributed methods. The saddle point of the primal-dual Lagrangian-based methods could not always lead to the optimal solution, despite their more general structure [10]. The most well-known distributed method over recent years is ADMM due to its flexible structure and advantage of convergence to the optimum point after finite iterations [11]. However, in this paper, a new approach based on the primal-dual method of multipliers (PDMM) is suggested as a distributed optimization method. Some experiments in the literature show the superiority of PDMM in terms of convergence rate [12] and less sensitivity to the auxiliary parameters [13] over the ADMM in several types of optimization problems. In addition, ADMM is derived from Douglas–Rachford splitting, while PDMM is derived from Peaceman–Rachford splitting, which has the fastest convergence bound for a part of optimization problems. The formulation of the problem statement over a graph is another difference between these two methods. Exchanging sensitive information among the entities is one of the main challenges of distributed approaches that can endanger the privacy of the agents. To overcome this problem, a proper formulation of the problem statement is required to preserve the privacy of the agents. The PDMM formulation presents an adequate form for this purpose by exchanging two vectors called public and private vectors between the connected agents. The proposed

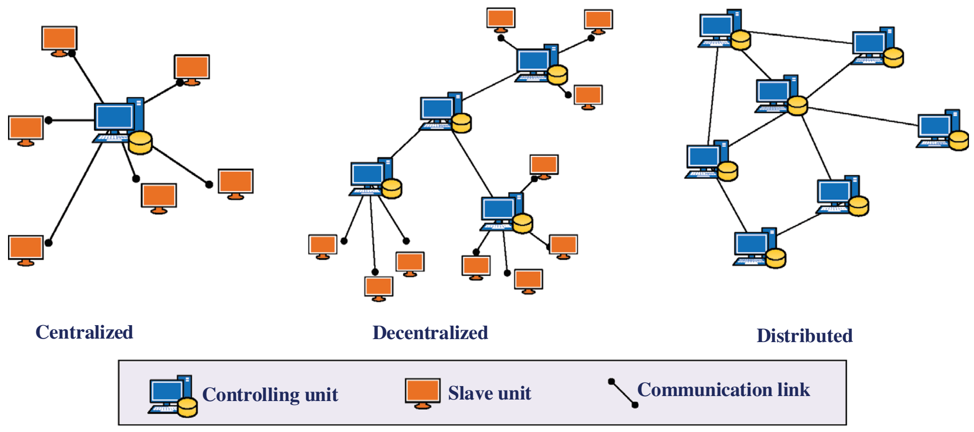

FIGURE 1 Classification of methods used for NMGs operation. Schematic illustration of centralized, decentralized, and distributed methods.

framework aims to address the deficiencies mentioned above by employing a distributed scheme based on the PDMM.

In recent years, distributed energy management systems have become increasingly significant due to the proliferation of distributed energy resources (DERs), microgrids, and the growing need for decentralized control in power systems. Some of the remarkable pieces of research on distributed/decentralized power management systems are investigated in Table 1 as a taxonomy table. Researchers have explored various techniques to address the challenges associated with these systems, including privacy concerns, the need for a coordinator, cost function limitations, and proper communication and computation infrastructure.

This literature review discusses some of the key studies in this area, as classified by the taxonomy table provided.

1. Privacy concerns: Preserving the privacy of agents' sensitive information is critical in distributed systems. Several studies have proposed approaches that address privacy concerns. For instance, studies [16–18, 20–22] in the taxonomy table focus on privacy preservation in various contexts, such as communication networks, power dispatch, and cyber-physical systems. These studies ensure that sensitive information is protected while still enabling distributed optimization.
2. Need for a coordinator: Distributed systems aim to reduce reliance on centralized control, so eliminating the need for a coordinator is important. Studies [24] and [28] in the taxonomy table propose fully distributed methods for microgrid control that do not require a central coordinator. These methods allow for local computation and communication among agents, resulting in more efficient and decentralized control.
3. Cost function limitations: In distributed systems, certain cost functions may be challenging to optimize. For instance, non-quadratic cost functions can be difficult to handle using weighted-averaging-based approaches. Studies [14, 16, 17, 22], and [26] in the taxonomy table address this issue by proposing distributed optimization methods that can handle a variety of cost functions, including non-quadratic ones.
4. Communication and computation infrastructure: To enable distributed management systems, proper infrastructure for communication and computation is required. Studies [18, 22, 24], and [27] in the taxonomy table investigate this challenge by proposing different strategies, such as diffusion strategies, communication networks, and cooperative reinforcement learning algorithms.
5. Policy updates, monitoring, and punishment mechanisms: In distributed systems, updating policies and monitoring agents' behaviour are critical aspects to ensure system efficiency and stability. However, these mechanisms are often overlooked in the literature.

Despite these advancements, none of the studies in the taxonomy table comprehensively address all the challenges mentioned above. The proposed study in this paper aims to address these gaps by introducing a fully distributed, privacy-preserving method for optimal power scheduling in networked microgrids with DERs and ESSs, using a cloud-fog-device architecture. This method addresses privacy concerns, eliminates the need for a coordinator, can handle non-quadratic cost functions, and provides appropriate communication and computation infrastructure. Additionally, it proposes a central cloud-based architecture for policy updates, monitoring, and punishment mechanisms, while maintaining the distributed nature of the system. Therefore, the main contributions of the paper can be summarized as follows:

- Introduces a privacy-preserving distributed scheme based on PDMM for power scheduling of networked microgrids with DERs and ESSs, improving upon previous ADMM-based methods.
- Optimizes the scheduling problem without any leader, coordinator, or central commander, enabling fully distributed operation through local agent interactions and computations capable of solving various types of objective functions, including non-quadratic cost functions, which is an improvement over many existing methods.
- Proposes a cloud-fog-device-based architecture for efficient and secure information exchange in networked microgrids,

TABLE 1 Taxonomy of remarkable literature on future energy management systems.

Reference	Case study	Problem	Main focus	Methods	Type of system	Renewable energy resources and ESSs	Cyber-physical architecture
[14]	NMG	Economic dispatch	Developing algorithm	Model predictive control (MPC) scheme	Non-centralized	Yes, solar-based distributed generation, and storage units	No
[15]	Microgrid	Economic dispatch	Developing a fast algorithm	Distributed sliding mode control (DSMC) based secondary control	Distributed	Yes	No
[16]	Microgrids	Social welfare maximization problem	Privacy-preserving algorithm	Consensus-based distributed control strategy	Distributed	No	No
[17]	NMG	Economic dispatch	Privacy-preserving algorithm	Primal decomposition, and dual decomposition	Decentralized	Yes	No
[18]	Microgrid	Minimizing energy loss and operation cost	Forecasting and privacy preservation	ADMM, and accelerated ADMM	Distributed	Yes	Yes
[19]	Microgrid	Secondary level control for economic dispatch (ED) and frequency regulation	Developing control method	Distributed secondary control and distributed model predictive control	Distributed	Yes	No
[20]	NMG	Energy management considering grid constraints and physical limits	Privacy-preserving algorithm	Dual decomposition and distributed approach	Distributed	No	No
[21]	Microgrid	Privacy-preserving energy management	Privacy-preserving algorithm	Consensus-based algorithms, random-weighted privacy-preserving algorithm	Distributed	Yes, ESS	No
[22]	Energy trading system	Coordinated energy management	Privacy-preserving scalable algorithm	Multi-actor-attention-critic	Decentralized	Yes, PV and ESS	Yes,P2P trading platform
[23]	Multi-area electricity and natural gas systems	Day-ahead scheduling	Developing algorithm	ADMM with self-adaptive penalty parameters	Decentralized	Yes, wind farm	No
[24]	Islanded microgrids	Economic dispatch	Developing algorithm	Fully distributed	Fully distributed	Yes, ESS	Yes, cyber-physical architec-ture with a communi-cation network over the microgrid

(Continues)

TABLE 1 (Continued)

Reference	Case study	Problem	Main focus	Methods	Type of system	Renewable energy resources and ESSs	Cyber-physical architecture
[25]	Microgrids	Economic dispatch	Developing control method	Diffusion strategy, function approximation	Distributed	Yes	No
[26]	NMG	Energy management to minimize the aggregated operational cost	Developing algorithm	ADMM	Distributed	Yes, ESS	No
[27]	Smart grid	Economic dispatch	Developing algorithm, heterogeneity, privacy-preserving	Distributed gradient-descent algorithm	Distributed	No	Yes, privacy preservation for cyber-physical systems
[28]	NMG	Security control and economic dispatch (ED)	Developing algorithm	Hierarchical control scheme	Fully distributed	Yes	No

eliminating the need for investment in local databases and computing hardware.
- Offers a central cloud-based architecture for policy updates, monitoring, and enforcement of punishments for misbehaving agents, ensuring system reliability without compromising the distributed nature of the system.
- Validates the proposed method through simulations on both small-scale microgrid and large-scale networked microgrid with various DERs and ESSs, comparing the results to other centralized and distributed methods for efficiency evaluation.

The rest of the paper is organized as follows: the formulation of the power dispatch problem is explained in Section 3. Section 4 investigates the proposed distributed optimization scheme for the NMG operation. The suggested cloud-based framework is presented in Section 5 with the detailed duties of every layer, and the simulation results for the proposed problem are analyzed in Section 6.

2 | PROBLEM FORMULATION

The main problem addressed in this paper is to optimize the power scheduling of NMGs in a distributed fashion. To simplify the problem, graph theory is utilized to represent an NMG system as a graph with multiple nodes and edges. This section first explains the graph theory and the assumptions made in the paper. Then, the conventional power scheduling formulation is investigated through two separate sections: the objective function and constraints. Finally, the distributed form of the problem is reformulated to have a better vision of the main distributed problem.

2.1 | Graph theory and problem assumptions

The proposed NMG consists of several MGs and each MG contains some areas [29]. Each area covers some dispatchable (MT and FC) and non-dispatchable (photovoltaics [PV] and wind turbines [WT]) DERs as well as ESSs with local loads. The proposed system can be illustrated as a graph with a set of nodes v and a set of edges E. In this paper, each node is assumed as an agent (area), and edges are assumed as the tie-lines between neighbouring agents. In the graph theory, every two nodes connected through an edge are assigned as neighbours. The neighbours of the ith agent are shown as bellows:

$$N(i) = \{\forall j \in v | (i,j) \in E\} \tag{1}$$

The number of neighbours of the ith agent is shown by N_i as the node degree. It is worth noting that v_i is used to show the agent i, and v^{batt}, v^{grid}, and v^{DG} show the sets of agents containing an ESS, the main grid and a dispatchable generator (e.g. MT and FC), respectively. We assume that each agent includes only one adjustable unit (main grid, ESS, or dispatchable DER) or an aggregation of several non-dispatchable units and an adjustable unit to avoid power shortage issues.

2.2 | Objective function

The objective function aims to minimize the total cost of power generation of the NMG through a period of time including generated power of dispatchable and non-dispatchable DERs as well as the amount of purchasing power from ESSs and the main grid [30]:

$$\min \sum_{t\in\tau}\sum_{i\in\nu}\text{Cost}_{i,t} = \min \sum_{t\in\tau}\left(\begin{array}{l} b^{\text{grid}}_{g,t}P^{\text{grid}}_{g,t} + \sum_{b\in\nu^{\text{batt}}} b^{\text{batt}}_{b,t}P^{\text{batt}}_{b,t} + \\ \sum_{d\in\nu^{\text{DG}}} b^{\text{DG}}_{d,t}P^{\text{DG}}_{d,t} + \sum_{i\in\nu}\sum_{n\in\nu_i} b^{n\text{disp}}_{i,n,t}P^{n\text{disp}}_{i,n,t}\end{array}\right) \quad ;\forall g\in\nu^{\text{grid}} \tag{2}$$

The amount of purchasing power from the grid $P^{\text{grid}}_{g,t}$ or ESSs$P^{\text{batt}}_{b,t}$can be positive or negative. In case of power shortage or economic priorities, extra amounts of power would be purchased from these sources and imported to the NMG by positive values. On the other side, the generated power by the NMG would be sold to the grid or ESSs which are represented by negative values in Equation (2), in case of extra power generation or economic reasons. Keeping in mind according to an incentive-based plan for encouraging investment in renewable energy resources, it is assumed that all the power generated by PVs and WTs is consumed at each time interval. Also, the output power of those units is forecasted. The nonlinear relationship between the input wind speed and the output power of a WT can be formulated as follows [31]:

$$P^{\text{wind}} = \begin{cases} 0 \quad v \le V_{\text{ci}} \; or \; v \ge V_{\text{co}} \\ \frac{1}{2}\rho A C_{\text{P}} v^3 = k_{\text{w}} v^3 \quad V_{\text{ci}} \le v \le V_{\text{r}} \\ P_{\text{r}} \quad V_{\text{r}} \le v \le V_{\text{co}} \end{cases} \tag{3}$$

Where ρ, A, and C_{p} are the air density, sweep area of the wind rotor, and power coefficient of the wind turbine, respectively, which presented as a lumped coefficient k_{w}. The nonlinear relationship between PV output power and irradiance and temperature can be considered as follows [32]:

$$P^{\text{PV}} = \eta \text{SI}\left(1 - 0.005\left(T + 25\right)\right) \tag{4}$$

Where, η, S, I, T are the efficiency of PV, area of PV cells, irradiance, and ambient temperature.

Therefore, the last term of the above equation ($\sum_{i\in\nu}\sum_{n\in\nu_i} b^{n\text{disp}}_{i,n,t}P^{n\text{disp}}_{i,n,t}$) is assumed as a constant value and is represented as $K^{n\text{disp}}_t$in the following reformulation of Equation (2):

$$\min \sum_{t\in\tau}\sum_{i\in\nu}\text{Cost}_{i,t} = \min \sum_{t\in\tau}\left(b^{\text{grid}}_{g,t}P^{\text{grid}}_{g,t} + \sum_{d\in\nu^{\text{DG}}} b^{\text{DG}}_{d,t}P^{\text{DG}}_{d,t} + \sum_{b\in\nu^{\text{batt}}} b^{\text{batt}}_{b,t}P^{\text{batt}}_{b,t} + K^{n\text{disp}}_t\right) \quad ;\forall g\in\nu^{\text{grid}} \tag{5}$$

2.3 | Constraints

The first and major mission of an NMG is to supply the load demand considering the limitations of the unit. Thus, the power balance equation should be considered as follows [30]:

$$P^{\text{grid}}_{g,t} + \sum_{d\in\nu^{DG}} P^{\text{DG}}_{d,t} + \sum_{b\in\nu^{batt}} P^{\text{batt}}_{b,t} + \sum_{i\in\nu}\sum_{n\in\nu_i} P^{n\text{disp}}_{i,n,t} = \sum_{i\in\nu} P^{\text{load}}_{i,t} \quad ; \; \forall t\in\tau \tag{6}$$

This equation announces that the equality constraint of power generation and consumption should be met in each period of time. The main grid, as well as the dispatchable generators, should be operated in their permitted ranges as:

$$P^{\text{grid, min}}_{g} \le P^{\text{grid}}_{g,t} \le P^{\text{grid,max}}_{g}; \quad \forall g\in\nu^{\text{grid}}, \forall t\in\tau \tag{7}$$

$$P^{\text{DG,min}}_{d} \le P^{\text{DG}}_{d,t} \le P^{\text{DG,max}}_{d}; \quad \forall d\in\nu^{\text{DG}}, \forall t\in\tau \tag{8}$$

The charge and discharge states of ESSs should be considered as follows [25]:

$$P^{\text{ch,max}}_{b} \le P^{\text{batt}}_{b,t} \le P^{\text{disch,max}}_{b} \quad ;\forall b\in\nu^{\text{batt}}, \forall t\in\tau \tag{9}$$

$$\begin{array}{l} E^{\text{batt}}_{b,t} = E^{0}_{b} - \sum_{\psi=1}^{t} P^{\text{batt}}_{b,\psi}\Delta t \quad ;\forall b\in\nu^{\text{batt}}, \forall t\in\tau \\ E^{\text{batt,min}}_{b} \le E^{\text{batt}}_{b,t} \le E^{\text{batt,max}}_{b} \quad ;\forall b\in\nu^{\text{batt}}, \forall t\in\tau \end{array} \tag{10}$$

These limitations express that in addition to satisfying the limited ranges of charging and discharging, the storing energy capacity and initial energy stored in the ESS should also be considered as Equation (10). The capacity of the transmission tie-lines between any two neighbouring agents forms another constraint as follows:

$$P^{L,\text{min}}_{ij} \le P_{ij,t} \le P^{L,\text{max}}_{ij} \quad ; \quad \forall i\in\nu, \forall j\in N(i), \forall t\in\tau \tag{11}$$

The power losses in the tie-lines of NMG are neglected. Therefore, any two agents should get into an agreement for power exchange as follows:

$$P_{ij,t} + P_{ji,t} = 0 \; ; \quad \forall i\in\nu, \; \forall j\in N(i) \tag{12}$$

So far, all required formulations to solve the optimal power dispatch of an NMG are explained. However, we need a distributed representation of these formulations based on the transmission powers (as the PDMM variables which are explained later in Section 4) between the neighbouring agents. To envisage the general formation of the proposed problem, Figure 2 shows a graphic diagram of lines, generation units, and local load demand in an agent. The output power generation of

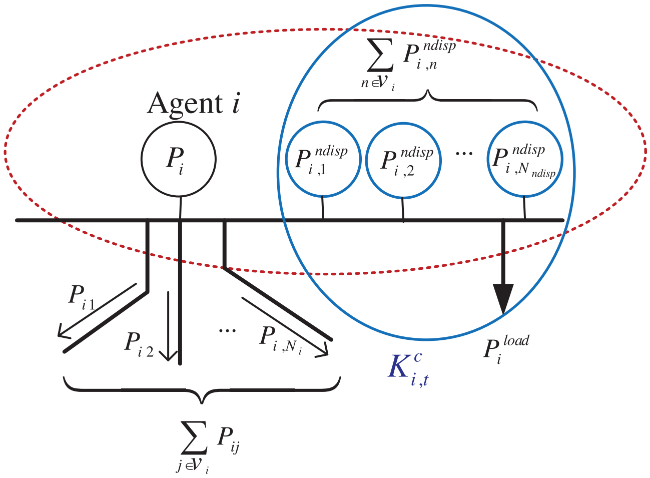

FIGURE 2 Schematic illustration of generation units, transmission lines, and local load demand in the ith agent of a microgrid.

the i-th agent based on the figure would be obtained as follows:

$$P_{i,t} = \sum_{j\in N(i)} P_{ij,t} - \sum_{n\in v_i} P_{i,n,t}^{ndisp} + P_{i,t}^{\mathrm{load}}; \quad \forall i \in v, \forall t \in \tau \tag{13}$$

where $P_{i,t}$ is a general index for power generation of an adjustable unit situated in the i-th agent of the NMG (keeping in mind that each agent includes one adjustable unit). In other words, it can be $P_{g,t}^{\mathrm{grid}}$, $P_{d,t}^{\mathrm{DG}}$, or $P_{b,t}^{\mathrm{batt}}$.

The output power of non-dispatchable units as well as the local load demand of an agent are forecasted and thus may lead to a general and constant value as:

$$\sum_{n\in v_i} P_{i,n,t}^{ndisp} - P_{i,t}^{\mathrm{load}} = K_{i,t}^{\mathrm{c}}; \forall i \in v, \forall t \in \tau \tag{14}$$

Similarly, the constraints explained in Equations (7) to (10) are reformulated as follows:

$$P_t^{\mathrm{grid,min}} + K_{g,t}^{\mathrm{c}} \le \sum_{j\in N(g)} P_{gj,t} \le P_t^{\mathrm{grid,max}} + K_{g,t}^{\mathrm{c}}; \quad \forall g \in v^{\mathrm{grid}}, \forall t \in \tau \tag{15}$$

$$P_d^{\mathrm{DG,min}} + K_{d,t}^{\mathrm{c}} \le \sum_{j\in N(d)} P_{dj,t} \le P_d^{\mathrm{DG,max}} + K_{d,t}^{\mathrm{c}}; \quad \forall d \in v^{\mathrm{DG}}, \forall t \in \tau \tag{16}$$

$$P_b^{\mathrm{ch,max}} + K_{b,t}^{\mathrm{c}} \le \sum_{j\in N(b)} P_{bj,t} \le P_b^{\mathrm{disch,max}} + K_{b,t}^{\mathrm{c}}; \quad \forall b \in v^{\mathrm{batt}}, \forall t \in \tau \tag{17}$$

$$\begin{aligned} E_{b,t}^{\mathrm{batt}} &= E_b^0 - \sum_{\psi=1}^{t}\left(\sum_{j\in N(b)} P_{bj,\psi} - K_{b,\psi}^{\mathrm{c}}\right)\Delta t; \quad \forall b \in v^{\mathrm{batt}}, \forall t \in \tau \\ E_b^{\mathrm{batt,min}} &\le E_{b,t}^{\mathrm{batt}} \le E_b^{\mathrm{batt,max}}; \quad \forall b \in v^{\mathrm{batt}}, \forall t \in \tau \end{aligned} \tag{18}$$

3 | PROPOSED DISTRIBUTED FRAMEWORK BASED ON PDMM

This section presents the required scheme to gain the optimal solution for power scheduling of NMGs using the PDMM after a short explanation of the PDMM preliminaries.

3.1 | Primal-dual method of multipliers

The PDMM is a distributed optimization method for a multi-agent system in which the agents solve a minimization problem by exchanging information and executing local computations. Based on the graph theory, we can represent a multi-agent system as a graph, in which agents are assumed as nodes and the existing connection between every two agents is considered as an edge. The PDMM is trying to solve a minimization problem in the following form [12]:

$$\begin{aligned} &\min \sum_{i\in v} f_i(\vec{x_i}) \\ &\text{s.t.} \quad \mathbf{A_{ij}}\vec{x_i} + \mathbf{A_{ji}}\vec{x_j} = \vec{c_{ij}}; \quad \forall i \in v,\ \forall j \in N(i) \end{aligned} \tag{19}$$

That means, every agent tries to minimize an objective function based on a vector of local variables as $\vec{x_i}$, subject to equality constraints in relationship with its neighbouring agents ($\mathbf{A}_{ij}\vec{x_i} + \mathbf{A}_{ji}\vec{x_j} = \vec{c_{ij}}$(, which are called consensus constraints.

Now, to solve the problem, each agent sends two vectors of variables to its neighbouring agents, called PDMM variables as $\vec{\lambda_{ij}}$and $\vec{x_i}$. The $\vec{\lambda_{ij}}$ is called the private PDMM variable and $\vec{x_i}$ is the public PDMM variable. These variables illustrate the status of the agent and are updated using local computations and having the PDMM variables of the neighbours, as follows [12]:

$$\begin{aligned} \overrightarrow{x_i^{k+1}} = \arg\min_{x_i} \Bigg\{ & f_i(\vec{x_i}) + \sum_{j\in N_i} \frac{1}{2} \left\| \mathbf{A}_{ij}\vec{x_i} + \mathbf{A}_{ji}\overrightarrow{x_j}^k - \vec{c_{ij}} \right\|_{\gamma_{ij}}^2 \\ & - \vec{x_i}^T \left(\sum_{j\in N_i} \mathbf{A}_{ij}{}^T \vec{\lambda}_{ji}^k \right) \Bigg\} \end{aligned} \tag{20}$$

$$\overrightarrow{\lambda_{ij}^{k+1}} = \vec{\lambda}_{ji}^k - \gamma_{ij}{}^{-1}\left(\mathbf{A}_{ij}\vec{x_i} + \mathbf{A}_{ji}\overrightarrow{x_j}^k - \vec{c_{ij}}\right); \forall i \in v, \forall j \in N(i) \tag{21}$$

After several iterations, a consensus is reached among the agents, and the main problem (19) is solved using the PDMM.

3.2 | PDMM for optimal power dispatch

Now, to use the PDMM for power scheduling of the NMG, we need to reform the main problem formulations mentioned in Section 3 into the PDMM format (19). Besides, we should keep in mind to set insensitive data as the public PDMM variables to preserve the privacy of agents against their peers. To this aim, the amount of tie-line power between every two areas is considered as the public variable at each time interval ($P_{i,j,t}$), which is insensitive data. Thus, the distributed optimization problem mentioned in Section 3 is rewritten as follows:

$$\begin{aligned} &\min \sum_{i\in \nu} f_i(P_{i,j,t}) \\ &\text{s.t.} P_{i,j,t} + P_{j,i,t} = 0 \\ &(13)-(16) \end{aligned} \tag{22}$$

The PDMM consensus constraint is defined as $P_{i,j,t} + P_{j,i,t} = 0$ that is mentioned earlier in Equation (12). The PDMM variables are updated iteratively based on Equations (20) and (21) as follows:

$$\begin{aligned} P_{i,j,t}^{\text{Iter}+1} = \underset{P_{i,j}^{G}}{\arg\min} &\left\{ f_i(P_{i,j,t}) + \sum_{j\in \nu^N} \frac{1}{2} \left\| P_{i,j,t} + P_{j,i,t}^{\text{Iter}} \right\|_{\gamma_{ij}}^2 \right. \\ &\left. - P_{i,j,t} \left(\sum_{j\in \nu^N} \lambda_{ji}^{\text{Iter}} \right) \right\}, \\ \forall i \in \nu^F, \forall j \in \nu^N, \forall t \in \tau \end{aligned} \tag{23}$$

$$\begin{aligned} &\lambda_{j,i,t}^{\text{Iter}+1} = \lambda_{ji}^{\text{Iter}} + {\gamma_{i,j,t}}^{-1} \left(-P_{i,j,t}^{\text{Iter}+1} - P_{j,i,t}^{\text{Iter}} \right) \\ &; \forall i \in \nu^F, \forall j \in \nu^N, \forall t \in \tau \end{aligned} \tag{24}$$

In each iteration, every agent calculates Equations (23) and (24) considering the limitations Equations (15) to (18) based on the type of agents. Besides, the function $f_i(P_{i,j,t})$ in Equation (23) is referred to the local cost minimization of each agent. In other words, the objective function (5) is formulated in Equation (25) which can be broken into the number of agents as their local functions as Equations (26) to (28) for various types of agents:

$$\begin{aligned} \sum_{i\in \nu} f_i\left(P_{i,j,t}\right) = &\sum_{t\in\tau} \left(b_{g,t}^{\text{grid}} P_{i,j,t} \right) + \sum_{t\in\tau} \sum_{b\in \nu^{\text{batt}}} b_{b,t}^{\text{batt}} \left(P_{i,j,t} \right) \\ &+ \sum_{t\in\tau} \left(\sum_{d\in \nu^{\text{DG}}} b_{d,t}^{\text{DG}} P_{i,j,t} \right) + \sum_{t\in\tau} K_t^{n\text{disp}} \end{aligned} \tag{25}$$

$$\int_{i\in \nu^{\text{grid}}} \left(P_{i,j,t}\right) : \sum_{t\in\tau} \left(b_{g,t}^{\text{grid}} P_{i,j,t} \right) \tag{26}$$

$$\int_{i\in \nu^{\text{batt}}} \left(P_{i,j,t}\right) : \sum_{t\in\tau} \left(\sum_{b\in \nu^{\text{batt}}} b_{b,t}^{\text{batt}} P_{i,j,t} \right) \tag{27}$$

$$\int_{i\in \nu^{\text{DG}}} \left(P_{i,j,t}\right) : \sum_{t\in\tau} \left(\sum_{d\in \nu^{\text{DG}}} b_{d,t}^{\text{DG}} P_{i,j,t} \right) \tag{28}$$

4 | CLOUD-FOG-DEVICE FRAMEWORK

This section proposes a cyber-physical architecture based on a cloud-fog-device model to ensure the privacy of data transactions in the optimal operation of the NMG in a distributed manner. The proposed framework enables real-time monitoring of the system's components while preserving the units' privacy. The framework consists of three main layers: the cloud layer, the fog layer, and the device layer. The cloud and fog layers represent the cyber layers, while the physical layer includes the equipment (generation and consumption units as well as the sensors). In the proposed NMG, the characteristics of these three layers are as follows:

4.1 | Device layer

This layer comprises the physical components such as dispatchable and non-dispatchable units, loads, and metering devices. The fog layer commands determine the operational state of the units in this layer based on their real-time status, which is shared with the fog and the NMG requirements [33]. In this paper, the consensus status obtained from the fog layer is applied to the actuators of the units in this layer, and their real-time data is collected from their sensors and transmitted to the upper layer for future processes.

4.2 | Fog layer

This layer is located near the device layer, with only one hop distance, which ensures high communication speed and low latency and jitter. The fog layer is responsible for the local monitoring, processing, and storage of data collected from the device and cloud layers. In this paper, the fog layer is responsible for constructing and covering each agent of the system. It gathers the component statuses of its agent and exchanges them with neighbouring agents using the cloud layer to achieve convergence, and the final outcome is applied to the device layer. It should be noted that this layer has a low-capacity local storage system to store the short-term condition of local devices and perform computations. Entities can communicate with this layer through wired technologies such as optical fibres and

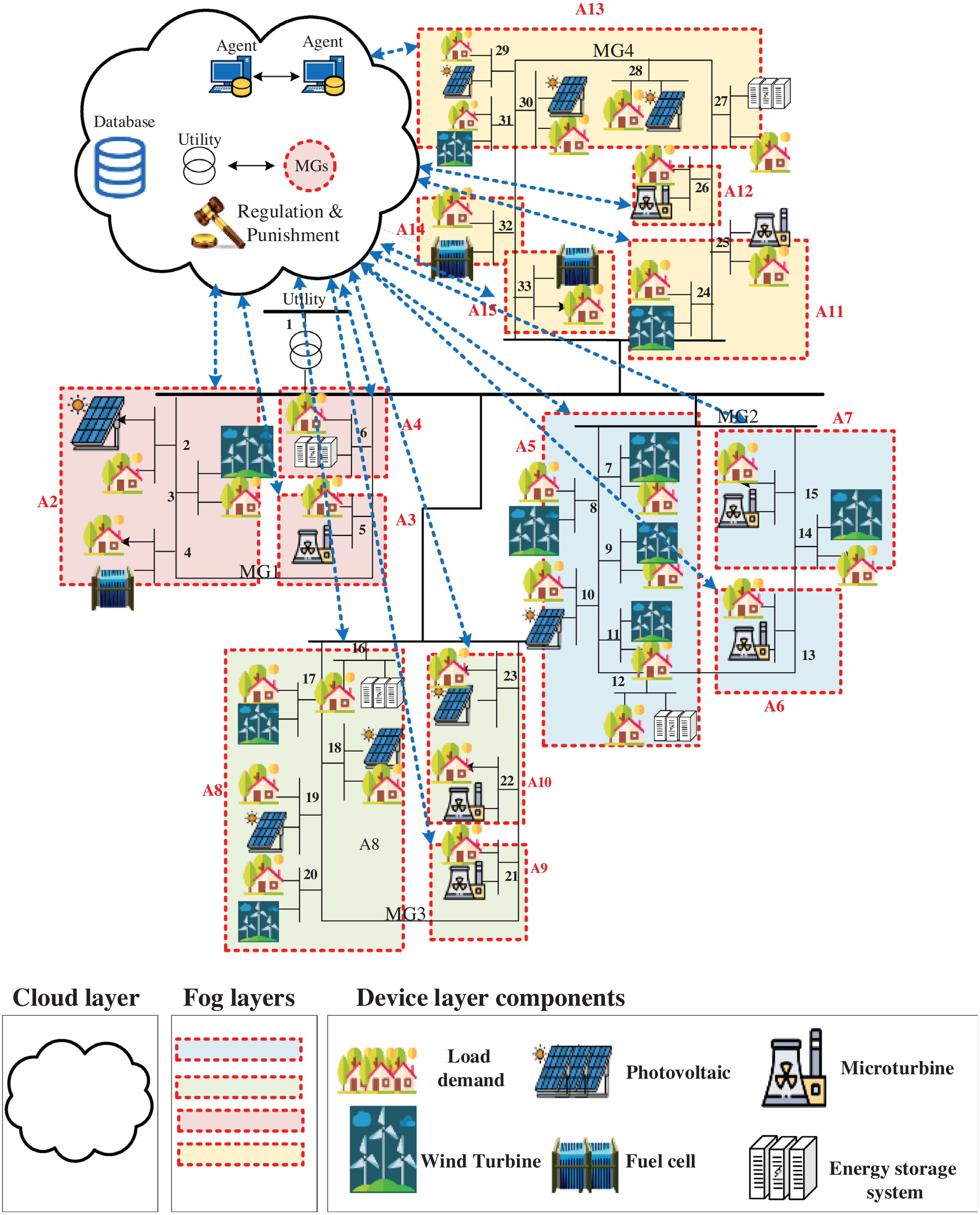

FIGURE 3 The proposed cloud-fog-based architecture.

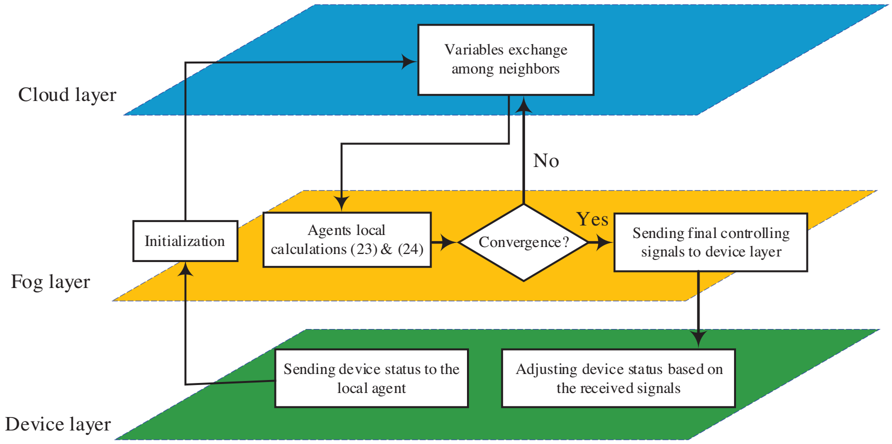

FIGURE 4 Flowchart of the proposed cloud-fog-based framework.

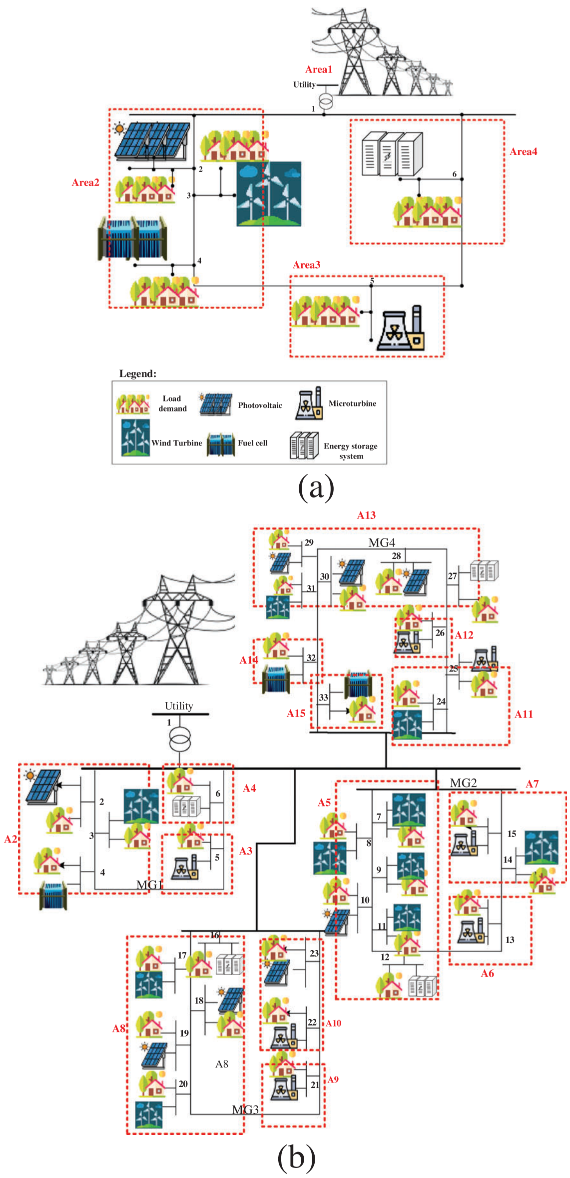

FIGURE 5 The proposed a) six-bus test microgrid test system with four agents b) 33-bus NMG schematic with 4 MGs and 15 agents.

Ethernet or wireless technologies such as ZigBee, satellite links, LTE, and IEEE 802.11. [34, 35]. The main local computations required to achieve the consensus target of the proposed method are executed in this layer.

4.3 | Cloud layer

The upper layer in the proposed NMG is the cloud layer, which has the capability of storing a large amount of data and high computing performance. This layer serves as a vast database for long-term analysis of the system, and it is the primary processor for computational and communication operations between every two agents in the MGs, between every two MGs, or between an MG and the DS. In each NMG system, a specific unit is assigned to regulate policies, execute punishment for delinquents, and update the management and computational rules for the cyber-physical components. The cloud layer is responsible for these duties. Policies are defined and executed in this layer, and new rules or computational developments for the other layers are updated here as well [34]. A schematic view of the suggested architecture is demonstrated in Figure 3 and a flowchart is shown in Figure 4 to illustrate the step-by-step implementation of the proposed framework divided by each layer.

5 | NUMERICAL RESULTS

In this section, the proposed framework is evaluated on two test systems. First, to assess the accuracy and speed of the proposed distributed operation system in comparison with well-known centralized schemes, a six-bus microgrid test system is simulated. Then, to observe the scalability and adjustability of the proposed method, a 33-bus NMG test system with 4 MGs and 15 agents (areas) is simulated for a 24-h time period in the presence of PVs, WTs, FCs, MTs, and ESSs using the proposed scheme. The proposed NMG test system is an extended version of typical microgrid test systems utilized in ref. [36] considering parameters of real generators and storage systems.

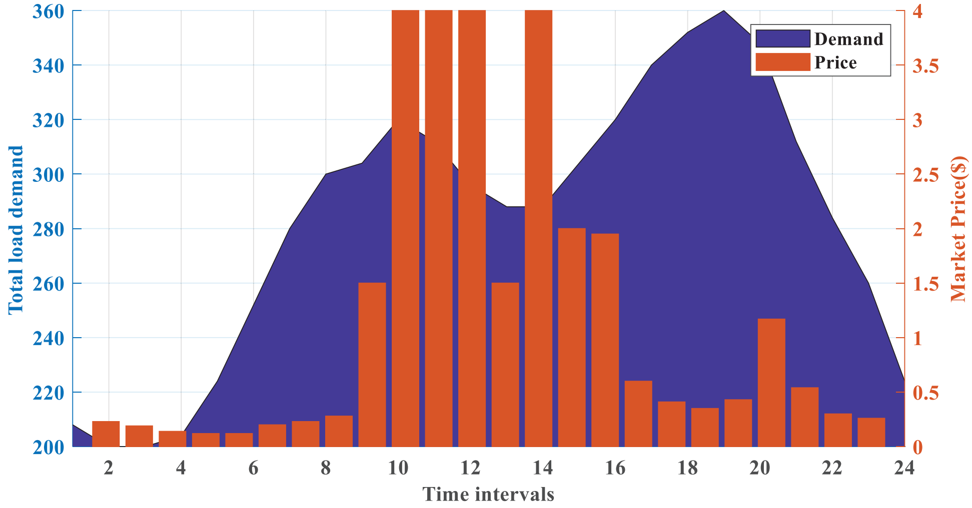

FIGURE 6 The total hourly load demand of the NMG and market power price.

TABLE 2 Parameters of the dispatchable units.

MG No.	Area No.	Agent type	$P_i^{min} - P_i^{max}$ (kW)	b_i (\$)	E^0 (kWh)	E^{max} (kWh)
MG1	Area2	FC	3-30	0.294	–	–
	Area3	MT	6-30	0.53	0	400
	Area4	ESS	−30-30	0.38	0	400
MG2	Area5	ESS	−20-20	0.36	–	–
	Area6	MT	4-28	2.584	–	–
	Area7	MT	3-35	0.711	–	–
MG3	Area8	ESS	−35-35	0.45	0	400
	Area9	MT	3-27	0.472	–	–
	Area10	MT	6-30	0.441	–	–
MG4	Area11	MT	0-24	0.515	–	–
	Area12	MT	6-30	0.491	–	–
	Area13	ESS	−20-20	0.28	0	400
	Area14	FC	0-18	0.332	–	–
	Area15	FC	5-30	0.345	–	–

Figure 5 shows the test systems and considers parameters of real generators and storage systems. Figure 5 displays the test systems.

The small-scale microgrid is assumed to be a part of the large-scale NMG (the first microgrid). The total load demand of the NMG and the power price of the main grid (considered as the first agent) at each time interval are presented in Figure 6. The dispatchable unit parameters are listed in Table 2.

The forecasted amounts of the output power of PVs, WTs, and load demands are illustrated in Figure 7. For simplicity, the output power of PVs and WTs in the existing 15 areas is considered as multiples of one particular profile (existing in the first microgrid/small-scale test system) but in accordance with their appearance in the areas. Therefore, for PVs, the multiplying factors are [1, 1.1654, 1.0529, 0.8390, 0.9114, 1.0188, 1.1830, 1.1860] for areas 2, 5, 8, 8, 10, 13, 13, and 13, and for WTs the multiplying factors are [1, 0.8107, 1.0547, 1.0802, 1.0036, 1.0273, 1.0229, 0.9177, 0.9966, 0.8514] in areas 2, 5, 5, 5, 5, 7, 8, 8, 11, and 13. The price for 1 kW power generation by PV or WT unit is assumed as \$2.55 and \$1.07, respectively. Initial values of PDMM variables $\overrightarrow{x_i}$ and $\overrightarrow{\lambda_{ij}}$ are assumed as zero vectors, γ_{ij} is considered as elementary matrix and ω is set on 0.1 using the trial and error method. All simulations are executed in MATLAB 2013a environment on an ordinary PC with an Intel(R) Core(TM) CPU @ 3.6 GHz, 32-GB RAM memory.

Remark: It is expected that distributed methods outperform centralized schemes in terms of convergence speed and information exchange in large-scale NMG operations. Distributed methods converge faster than centralized algorithms in large-scale NMGs due to their ability to parallelize computations and

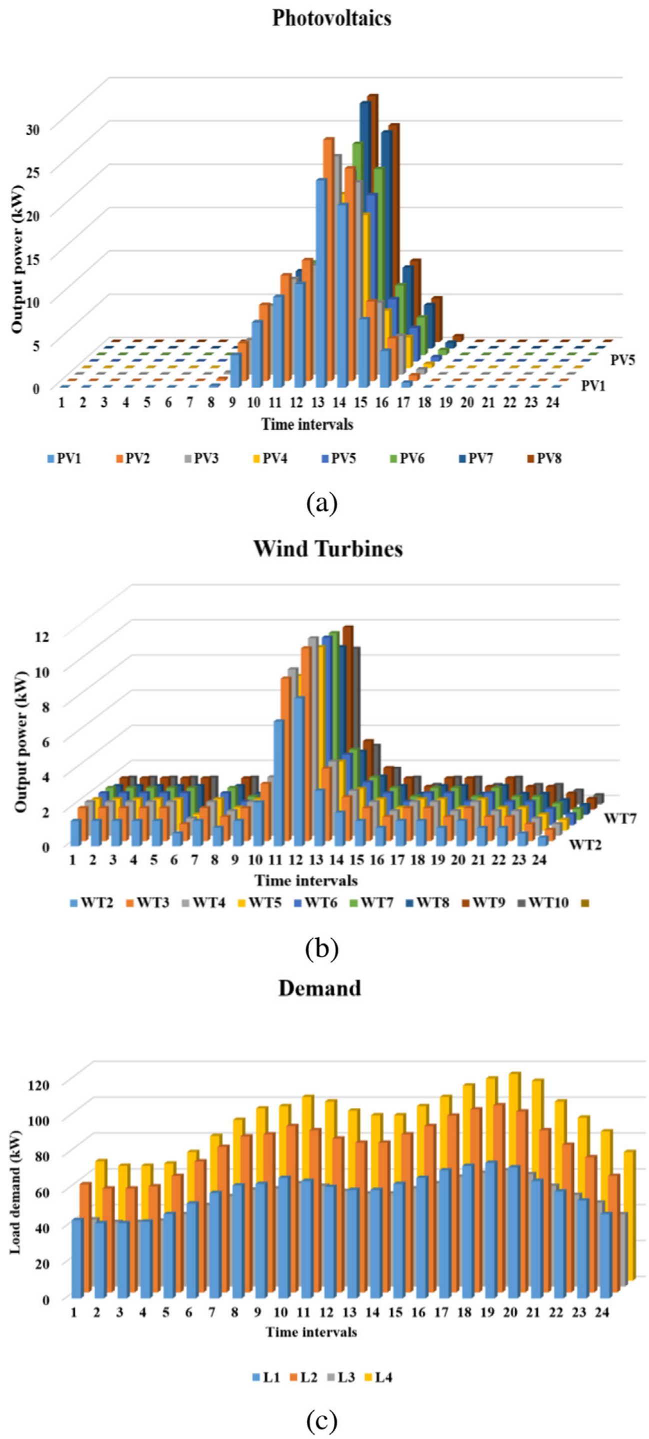

FIGURE 7 The main forecasted output power of a) PVs, b) WTs, and c) load demands in the NMG.

distribute them across multiple nodes. The distributed nature of the proposed method allows each agent to compute its own local solution, reducing the computational burden on any single node and enabling parallelization. Agents only need to communicate with their neighbours to exchange information, significantly reducing communication overhead. In summary, the parallelization and distributed nature of the proposed method allow for faster convergence and better scalability in large-scale NMGs compared to centralized algorithms.qwedee

5.1 | Small-scale microgrid

To assess the performance of the proposed method, the proposed method performance is compared with other powerful centralized (TLBO [37] and MTLBO [38]) and distributed (fully distributed ADMM [39, 40]) methods. The results of the comparison with the centralized method demonstrate how accurate the proposed method is. Since the aim is to have a fully distributed method that achieves the accuracy of the central algorithms. Besides, by comparing the proposed algorithm with the most prominent distributed algorithm (ADMM), the superiority of the method over other existing distributed algorithms is evaluated. To this end, the total cost of operation calculated using TLBO, MTLBO, and ADMM and compared with the proposed method and the related convergence rates can be observed in Figure 8 through 200 intervals. As is observable, the proposed method approaches the same optimal point as the MTLBO method very soon while the ADMM method achieves a fluctuating cost around the optimal point in Figure 9.

To draw a more subtle comparison of the methods, Table 3 demonstrates the final cost, total power mismatch, mean average error (MAE) of power mismatch, and required iterations to reach the convergence which are calculated using the fully-distributed ADMM and centralized methods including TLBO and MTLBO. The table clearly demonstrates the fast convergence performance of the proposed method in comparison to the ADMM method. Furthermore, the accuracy of the proposed scheme is obvious through the calculated errors and operation costs. The proposed scheme achieves the optimal solution of the MTLBO in 500 iterations with negligible error and the ADMM reaches roughly the same cost in 881 iterations. This shows the accuracy and fast response of the proposed method for a small-scale microgrid test system.

The small-scale experiment results demonstrate that the proposed distributed method is highly accurate and converges quickly to the optimal solution. The results show that the proposed method performs comparably to the centralized TLBO and MTLBO algorithms, and outperforms the fully-distributed ADMM algorithm.

One interesting observation from the results is that the proposed method approaches the same optimal point of the MTLBO method very quickly. This indicates that the proposed method has the potential to achieve the same level of accuracy as centralized methods, while still operating in a fully distributed manner. Moreover, the proposed method demonstrates faster convergence than the fully-distributed ADMM algorithm, which is a widely-used distributed optimization method in power systems.

Overall, the results of the small-scale experiment demonstrate the effectiveness of the proposed distributed method in optimizing the power scheduling problem of microgrids. The proposed method provides an accurate and fast solution, while operating in a fully distributed manner. The method's ability

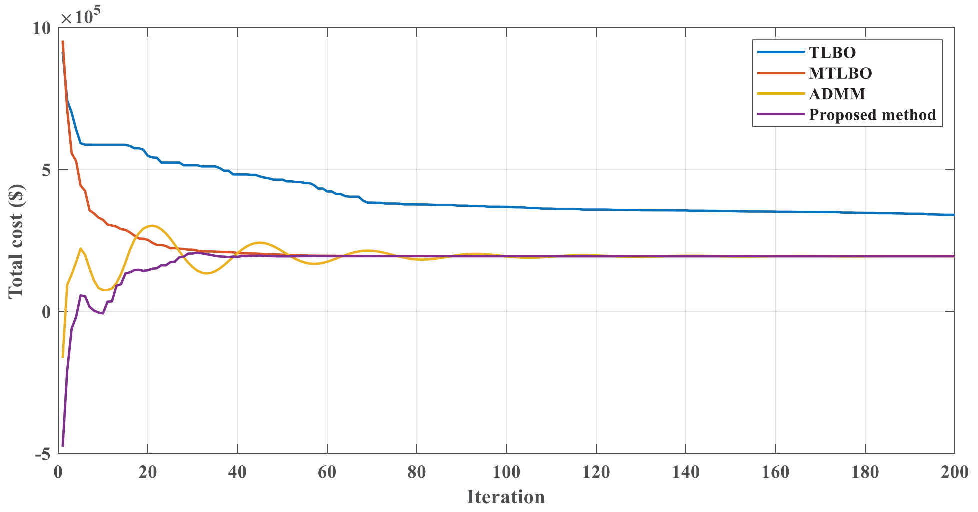

FIGURE 8 The total cost of operation gained by each method of operation of the small-scale microgrid through iterations.

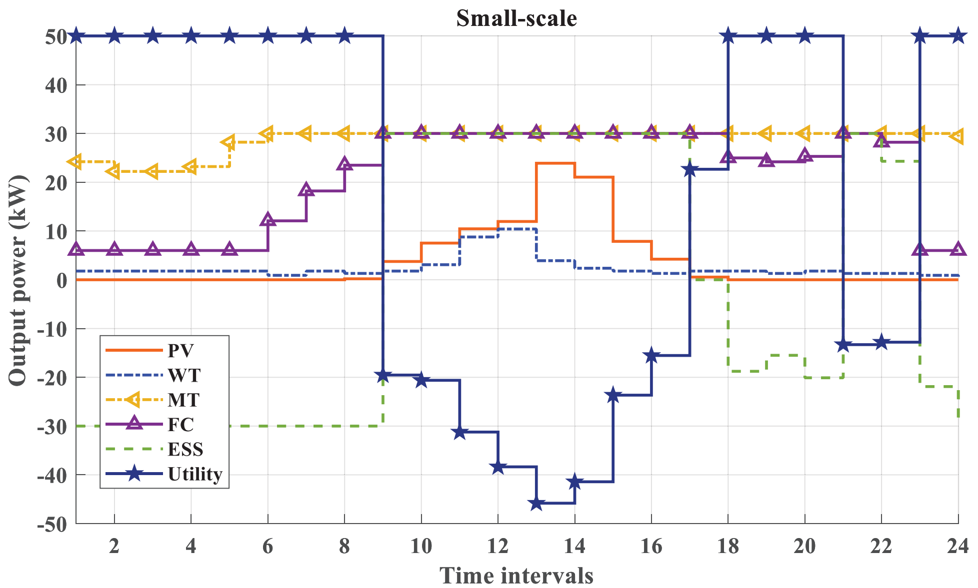

FIGURE 9 The day-ahead hourly scheduled output power of dispatchable units and non-dispatchable DERs in the small-scale microgrid.

to consider both dispatchable and non-dispatchable DERs as well as ESSs in an optimized manner further highlights its practicality and usefulness for real-world microgrid applications.

5.2 | Large-scale NMG

To evaluate the scalability of the proposed scheme, Table 4 provides a comparison between the distributed and centralized schemes discussed earlier for calculating the day-ahead optimal power scheduling of the NMG test system. The test system consists of 33 buses and 15 agents, with each agent having 24 specific status values to send to its neighbours, resulting in 360 variables to optimize considering the complexity of applying the ESSs constraints.

As shown in the table, the proposed method yields the most optimal cost among all the considered optimization methods, which is significantly better than the results obtained by the TLBO method. This highlights that the well-known TLBO method is not suitable for solving such complex NMG power optimization problems with 360 output variables.

In order to evaluate the proposed method, a modified version of TLBO (MTLBO) is used. The results show that MTLBO can converge to a value of 2.899×103$ in 1500 iterations, which is higher than the value obtained by the distributed methods (2.882×103$). The centralized methods achieve zero total power mismatch and zero mean absolute error (MAE) of the obtained power mismatch per interval values. Comparing the proposed method with the fully distributed ADMM method, it is observed that the proposed method achieves fewer amounts

TABLE 3 The comparison of the performance of the proposed method and fully-distributed ADMM approach, TLBO and MTLBO on the small-scale microgrid test system.

			Total obtained cost ($\times 10^3$\$)	Total power mismatch (kW)	Iterations to converge	MAE of power mismatch (kW)
Microgrid	Distributed	Proposed method	193.7688	1.8×10^{-5}	500	2.3×10^{-5}
		Fully dist. ADMM	193.7704	1.2×10^{-4}	881	2.5×10^{-4}
	Centralized	TLBO	429.6230	0	20,000	0
		MTLBO	193.7688	0	367	0

TABLE 4 The comparison of the performance of the proposed method and fully-distributed ADMM approach, TLBO and MTLBO on the large-scale NMG test system.

			Total obtained cost ($\times 10^3$\$)	Total power mismatch (kW)	Iterations to converge	MAE of power mismatch (kW)
Networked microgrid	Distributed	Proposed method	2.882587	1.7×10^{-4}	616	4.9×10^{-4}
		Fully dist. ADMM	2.882307	3.9950	695	0.1819
	Centralized	TLBO	3.635269	0	10,000	0
		MTLBO	2.899125	0	1500	0

of power mismatch and MAE over fewer iterations. The PDMM method has a near-zero total power mismatch, whereas ADMM has a 4 kW power mismatch. However, the total obtained cost of ADMM is almost the same as the proposed method, considering the power mismatch in ADMM. The proposed method's superiority over the fully distributed ADMM method in terms of accuracy is evident in Table 4. Although both methods approach the same optimal point, the proposed method achieves this with significantly less power mismatch, indicating that the proposed method is more precise in meeting the constraints of the NMG optimization problem. While the convergence speed advantage in Figure 8 may not be absolute, it is important to note that the proposed method still outperforms the fully distributed ADMM method in terms of convergence, considering accuracy.

Furthermore, Figure 10–13 show the optimal power dispatch of the utility and MGs based on an area division using the proposed method. The global results are obtained after 616 iterations to satisfy all constraints at every time interval. It is noteworthy that this CPU time is calculated by a single common PC for all agents in a unified framework. Therefore, according to the parallel (distributed) performance of the proposed framework, this CPU time will be shared among all agents which will get 16.7333 s for the whole process.

Moreover, the exporting/importing power of each microgrid and the utility are demonstrated in Figure 14. These amounts demonstrate the scheduled power exchanges of microgrids and utilities with each other during the day.

To provide an example of equality constraints for tie-lines, as mentioned in Equation (12), the power injected from agent 12 to agent 13 and the injected power from agent 13 to 12 at the 7th time interval are shown in Figure 15. It is evident from the figure that these values will eventually converge to the same values (6.79 kW) in opposite directions after 661 iterations.

To evaluate the accuracy of the proposed method, the total cost and the power-demand mismatch during a 24-h period (considered as the total error) are presented in Figure 16. The results demonstrate the convergence of the total cost to the optimum result and the total error to a small value (2.5−8% of the total load demand).

In summary, the proposed method exhibits high-speed and precise performance in solving the optimal power scheduling of NMGs in a distributed manner. The results obtained using the proposed method not only surpass the fully distributed ADMM method, but also challenge well-known centralized methods. Furthermore, the proposed scheme provides precise performance while preserving privacy in communication and distributed computation.

5.3 | Discussion

The simulation results demonstrate the effectiveness and superiority of the proposed distributed scheme in solving the day-ahead optimal power scheduling problem of NMGs with different renewable energy resources and energy storage systems. The proposed method allows for optimizing the power scheduling problem through local computation of agents and private communication between agents without any centralized scheduling unit, which reduces the dependence on a central authority and improves the privacy of the communication.

In the small-scale microgrid experiment, the proposed method achieves faster convergence in comparison to the fully-distributed ADMM and centralized TLBO and MTLBO methods, and is more accurate compared with ADMM. The proposed method outperforms ADMM in terms of MAE of power mismatch on a large scale and in terms of convergence speed on a small scale.

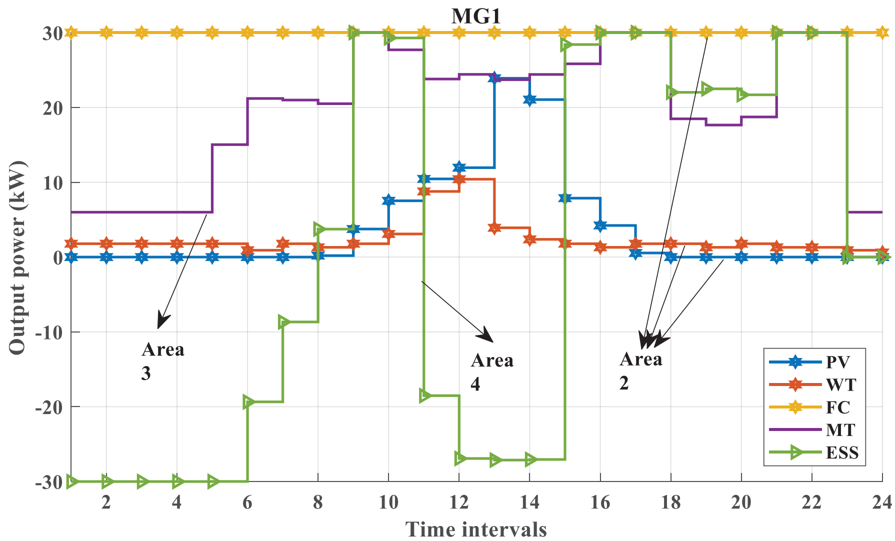

FIGURE 10 The day-ahead hourly scheduled output power of dispatchable units and non-dispatchable DERs in microgrid 1 of the NMG (area 2–4).

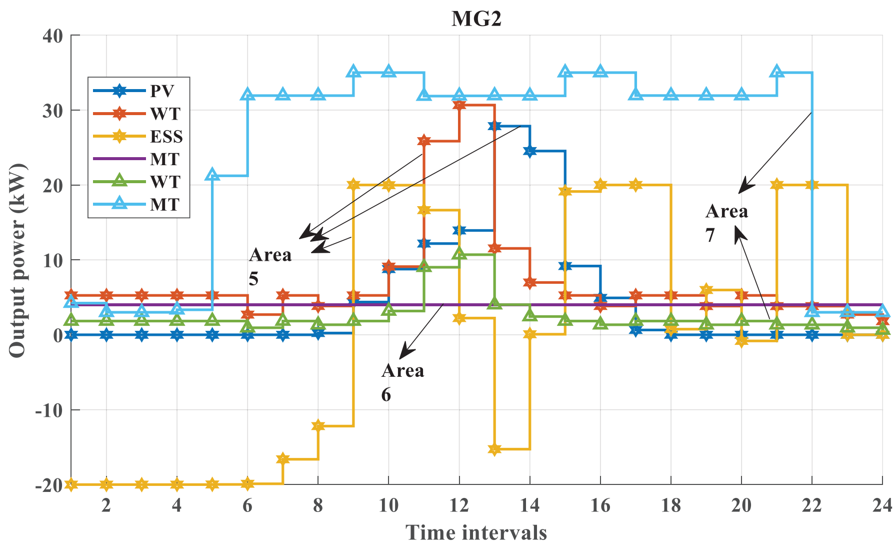

FIGURE 11 The day-ahead hourly scheduled output power of dispatchable units and non-dispatchable DERs in microgrid 2 of the NMG (area 5–7).

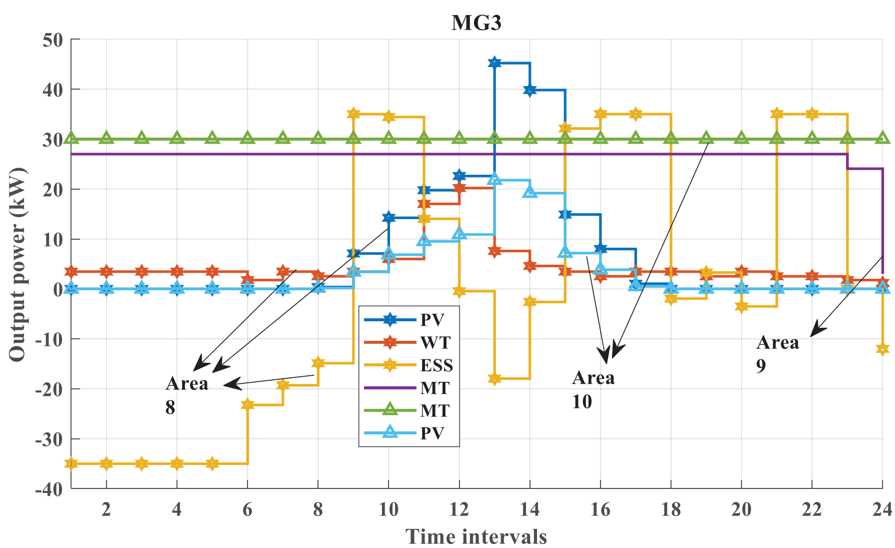

FIGURE 12 The day-ahead hourly scheduled output power of dispatchable units and non-dispatchable DERs in microgrid 3 of the NMG (area 8–10).

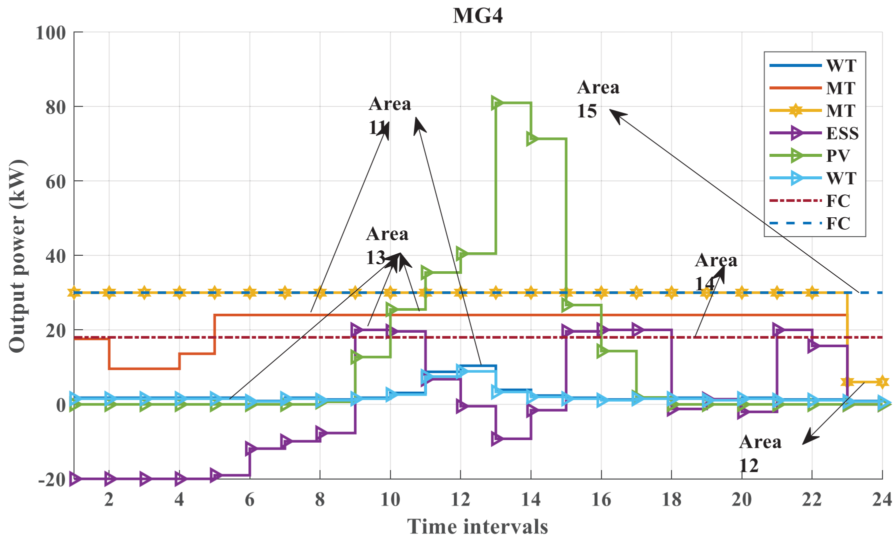

FIGURE 13 The day-ahead hourly scheduled output power of dispatchable units and non-dispatchable DERs in microgrid 4 of the NMG (area 11–15).

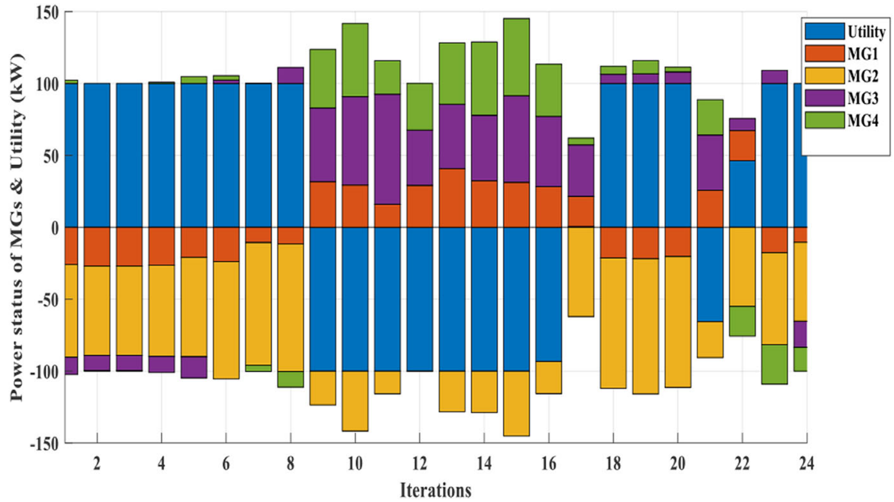

FIGURE 14 The day-ahead hourly scheduled output power of utility and each microgrid in the NMG.

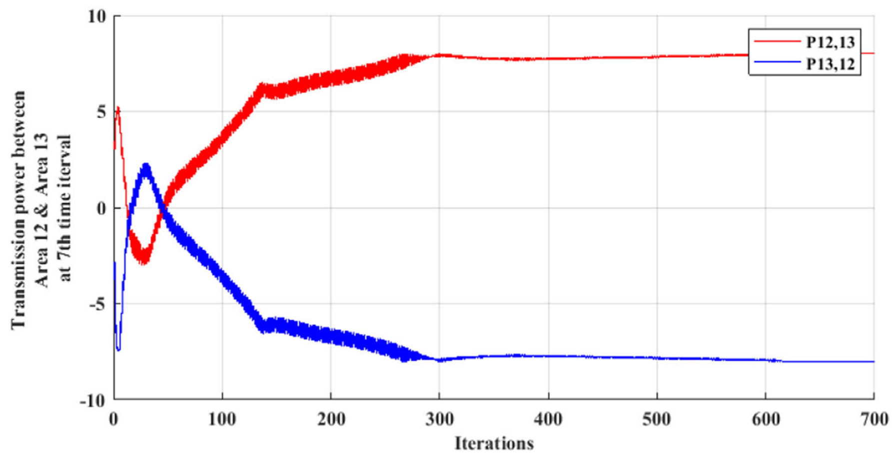

FIGURE 15 The tie-line power between agents 12 and 13.

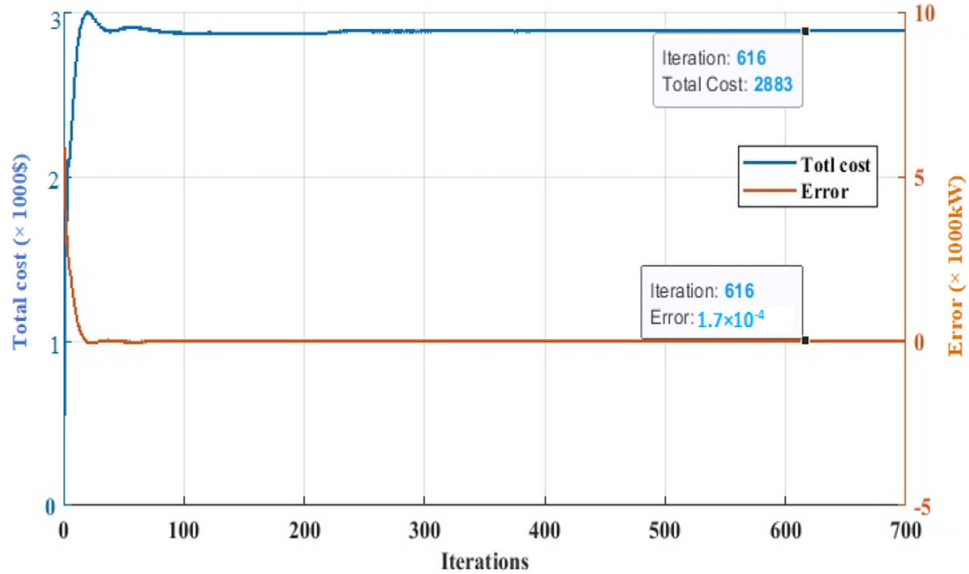

FIGURE 16 Total cost and total error trends through iterations.

Overall, the simulation results demonstrate the fast and precise performance of the proposed distributed scheme for networked microgrids, showing its scalability and convergence. The proposed cloud-fog-based framework can also provide a fast and economical infrastructure for the proposed distributed method.

6 | CONCLUSION

This paper proposes a framework for the distributed optimal power scheduling of NMGs based on a private cloud-fog-device architecture. The proposed framework utilizes a fully distributed PDMM-based approach to optimize the scheduling of NMGs while considering ESSs and renewable power plants. The cloud-fog-based structure ensures secure data transactions among MGs with efficient and low latency performance. The framework also includes a rule updating center and a centralized supervision system for units' behaviour to maintain security and ensure updated rules. The proposed framework eliminates the need for investment in local databases and ensures fast data communications. The proposed framework is evaluated on a small-scale microgrid and a large-scale NMG with 360 output variables that involve dispatchable and non-dispatchable DERs. Simulation results demonstrate the accurate and fast performance of the proposed framework in dealing with large-scale management and optimization problems, outperforming other existing fully distributed and centralized methods.

NOMENCLATURE

$\overrightarrow{\lambda_{ij}}$	The private variable vector of the *i*th agent to the *j*th agent (in the neighbourhood)
$P_{i,n}^{n\text{disp}}$	The output power of the *n*th non-dispatchable generator in the *i*th area
$\vec{x}_{ij}$	The *i*th agent's public PDMM variables vector
$\vec{b}_i$	The price vector of the *i*th area
$\overrightarrow{c_{ij}}$	PDMM parameters vector
b_b^{batt}	The bidding price of the *b*th ESS
b_d^{DG}	The bidding price of the *d*th dispatchable DER
b_g^{grid}	The bidding price of the main grid (utility)
Δt	Operation time interval
E_b^0	The initial energy of the *b*th ESS
$P_b^{\text{ch,max}}/P_b^{\text{disch,max}}$	The maximum amount of charge/discharge of the *b*th ESS
$\mathrm{A_{ij}}, \gamma_{ij}$	PDMM parameters matrices
$b_{i,n}{}^{n\text{disp}}$	The bidding price of the *n*th non-dispatchable generator in the *i*th area
Cost_i	Total cost for the *i*th agent
$E_b{}^{\text{batt}}$	The stored energy of the *b*th ESS
$E_b{}^{\text{batt,max}}/E_b{}^{\text{batt,min}}$	The maximum/minimum amount of the stored energy in the *b*th ESS
i, j	Indices for agents
k	Iteration index
K_i^c	The total forecasted power of the non-dispatchable generation and consumption (constant value) of the *i*th agent
n	Index of non-dispatchable units
$N(i)$	Set of the neighbours of the *i*th agent
Nei_{ij}	Index of the *j*th neighbour of the *i*th agent
N_i	Index of the numbers of the neighbours of the *i*th agent

Parameters

P_b^{batt} The charged/discharged power of the bth ESS
P_d^{DG} The output power of the dth dispatchable DER
$P_d^{\text{DG,max}}/P_d^{\text{DG,min}}$ The maximum/minimum output power of the dth dispatchable DER through the time
P_g^{grid} The exported/imported power of the upstream grid
$P_g^{\text{grid,max}}/P_g^{\text{grid,min}}$ The maximum/minimum exchangeable output power of the upstream grid
P_i Power generation of an adjustable unit situated in the ith agent
P_{ij} The tie-line power injected from agent i to agent j
$P_{ij}^{L,\text{max}}/P_{ij}^{L,\text{min}}$ The maximum/minimum tie-line power injected from agent i to agent j

Sets and indices

t,ψ Time indices
v Set of the system nodes

Variables

v^{batt}/b Set/index of ESSs
v^{DG}/d Set/index of the agents containing a dispatchable generator
v^{grid}/g Set/index of the upstream grid node
v_i, v_j Set of the ith and jth agent
τ Set of the time intervals

AUTHOR CONTRIBUTIONS

Seyede Zahra Tajalli: Conceptualization; Data curation; Formal analysis. Abdollah Kavousi-Fard: Investigation; Methodology; Project administration. Mohammad Mardaneh: Resources; Software; Supervision. Mazaher Karimi: Conceptualization; Supervision; Writing—review & editing.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

Data would be prepared as per request from the authors.

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