Electric Power Systems Research 214 (2023) 108806

Contents lists available at ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

A cloud edge computing method for economic dispatch of active distribution network with multi-microgrids

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ARTICLE INFO

Keywords:
Cloud edge computing
Multi-agent deep reinforcement learning
Economic dispatch
Active distribution F

ABSTRACT

In view of the risks and challenges of privacy data leakage and the communication burden in the traditional economic dispatch for active distribution network with multi-microgrids, this paper proposes a cloud edge computing method for economic dispatch of active distribution network with multi-microgrids. In this method, the cloud server is responsible for the calculation of active distribution network, and each edge server is in charge of the calculation of its own microgrid. The multi-agent deep reinforcement learning is employed to realize cloud edge collaborative computing, where each edge server and cloud server corresponds to an agent. Through case analysis, the reliability of the cloud edge computing method is confirmed. The simulation results show that the proposed method can provide a high-quality solution for economic dispatch of active distribution network with multi-microgrids on the premise of protecting data privacy and reducing the communication burden.

1. Introduction

Microgrids are connected to the active distribution network (ADN), which make full use of Distributed Generations (DGs) to reduce power generation costs [1–3]. Hence, more studies related with microgrid applications is proposed. A multi-objective control scheme [4] is presented that simultaneously ensures elimination of the collective active power oscillations / reactive power oscillations (APOs/RPOs) at point of common coupling (PCC), overcurrent protection and reactive power injection. An independently neutral current control approach [5] is proposed for the fourth leg of the vehicle to grid three phase four leg (V2G 3p4L) inverter to regulate the DC-link along with neutral current control capability. A new bi-level optimal scheduling model is proposed [6] for promoting the participation of battery swapping stations (BSSs) in regulating the isolated microgrid (IMG) economic operation.

As the inheritance and deepening of the microgrid, multi-microgrids (MMGs) are of great significance to improve the economic and ensure the reliability of regional load power supply of ADN [7]. In the past decades, the economic dispatch (ED) of ADN with MMGs is always an important research topic. For the ED of ADN with MMGs, the centralized model usually need the collection of the DGs parameters and the internal information of the MMGs [8]. The centralized model may lead to data leakage. Meanwhile, the large-scale operation data of ADN and MMG will also increase the communication burden.

To overcome the communication burden of centralized mode, distributed model for the ED of ADN with MMGs usually is adopted [9]. A lot of research has been done on the ED of ADN with MMGs based on distributed model. An autonomous optimization model of analytical target cascading theory (ATC) [10] is proposed to solve the ED of ADN with MMGs. The parallel solution of microgrid autonomy mode is achieved in this model. A dispatch model based on the bi-level optimal energy management (OEM) framework [11] is established, which reduces to the operation cost of both ADN and MMGs A distributed and fast ED method is provided to achieve the finite-time convergence to the optimal value [12], where the distribution network and microgrid are solved separately without considering the overall optimization. A decentralized robust model [13] is proposed to minimize the total operation cost through coordinated operation of ADN and MMGs. A multi-objective dispatch model [14] is proposed based on the decomposition algorithm to reduce operating costs. At present, the existing literature mainly focuses on the solution of ED model for ADN with MMGs, but the literature ignores the privacy protection of ADN and Microgrid.

However, as an independent stakeholder, ADN and microgrid do not hope to disclose the privacy of data to each other. Cloud edge computing can work out the problem of data privacy disclosure [15–17]. A cloud edge computing framework [18] is proposed to realize dynamic ED of microgrid, and its ED is conducted on a local digital signal processor

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https://doi.org/10.1016/j.epsr.2022.108806
Received 6 July 2022; Received in revised form 7 September 2022; Accepted 9 September 2022
Available online 16 September 2022
0378-7796/

(DSP) chip and a remote cloud computing platform (CCP). A edge intelligence (EI) structure [19] is proposed to solve the ED in virtual power plant (VPP) of internet of energy. The cloud edge computing framework [15,16] is formulated to relieve the computation burden, while the data privacy protection is not considered. In [20], a first production-level cloud-based power system simulation platform is developed to compute the ED, and its model of the ED saves the significant cost based on the system security and quality of service. In a cloud edge computing environment, machine-learning decision-making framework [21] is proposed for the ED of an islanding microgrid. In this method, the cloud server solves the optimal dispatch decision sequences, and the edge computing adopts well-trained model based on keeping the long-term parameters unchanged for implement the real-time microgrid energy dispatch. A cloud-edge cooperative dispatching (CECD) method [22] is provided, which alleviate the huge pressure on the modeling and computing of ADN. The cloud edge computing [17–19] is used for microgrid and ADN. However, the collaborative relationship between ADN and MMGs is not considered and analyzed in these methods. Based on the cloud-edge computing architecture, a data-driven anomaly identification method is proposed [23] to serve as a widely applicable and efficient line of defense against either cyber or physical anomalies. Centralized computing is initiated only when any edge device detects an anomaly while uploading relative measurements. However, the data of cloud server does not feed back to the edge server. This method is not suitable for the ED of ADN and MMGs with collaborative relationship. A cloud-edge cooperative method [24] is designed to integrate the voltage regulation and economic operation. This method focuses on the voltage issues by integrating the second-level and third-level priorities in a cloud-edge collaboration based hierarchical control method. All the data of system measurements are collected and analyzed by the cloud sever of incremental distribution networks. The transmission of a large amount of data may lead to data leakage and increase the network communication burden. A three-layer day-ahead optimal schedule is proposed [25] taking account of multi-stakeholders in ADN. However, the Interaction of the three layers increase the communication burden. Meanwhile, the transmission of a large amount of system information between the cloud server and the edge server may also lead to data leakage. In order to solve the privacy leakage problem of ADN and microgrid, this paper proposes a cloud edge computing method for ED of ADN with MMGs.

Since the multi-agent could corresponds to multiple edge servers and cloud server. It is appropriate that multi-agent deep reinforcement learning (MADRL) is employed to cloud edge computing. Furthermore, the MADRL is suitable for cooperation environment or competition environment. The MADRL is competent for the cloud edge computing. The multi-agent deep deterministic policy gradient (MADDPG) considers its own behavior and other agent strategies [26]. Aiming at the problem of traditional MADRL, the MADDPG completes complex tasks through collaborative decision-making in the dynamic environment [27–30]. A trajectory control algorithm based on the MADDPG [31] is proposed to address unmanned aerial vehicle (UAV)-aided mobile edge computing. Based on the MADDPG, an intelligent and efficient resource allocation and task offloading algorithm [32] is proposed to solve the energy-efficient task offloading and resource allocation for augmented reality (AR) in multi-mobile-edge computing systems. Based on the edge computing of MADDPG, a deep reinforcement learning algorithm [33] is proposed to address the problem that failure information cannot be promptly delivered.

At present, MADDPG has been successfully applied in different industries. However, cloud computing based on MADDPG has not been found to be applied to the ED of ADN with MMGs. In view of the limitation of existing research on the ED of ADN with MMGs, this paper proposes a cloud computing based on MADDPG for the ED of ADN with MMGs. The contributions of this paper can be summarized into the following three aspects:

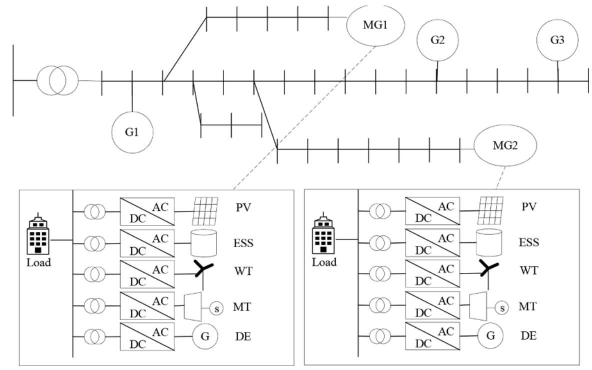

Fig. 1. Model of active distribution network with multi-microgrids.

a) To protect data privacy and reduce communication burdens, a method of cloud edge computing is proposed to solve the ED of ADN with MMGs, where the data is not transmitted between ADN and MMGs. In the method, the ED models of ADN and microgrid are established in the cloud server and edge server, respectively.
b) The MADDPG algorithm is adopted to realize cloud edge computing, where the cloud server and each edge server respond to each agent for handling the continuous and dynamic situation space in ADN with MMGs.
c) The proposed method can protect data privacy of ADN and MMGs, while the cost of ED is close to the global optimal value.

The remaining part of this paper is structured as follows: Section 2 presents model of cloud edge for the ED of the ADN with MMGs. In Section 3, the MADDPG algorithm is adopted to realize the cloud edge computing. Furthermore, case results are presented in Section 4. Finally, we get the conclusions in Section 5.

2. Cloud edge model for economic dispatch

2.1. Economic dispatch model

The model of the ADN with MMGs is briefly described to facilitate the subsequent analysis.

The model of the ADN with MMGs is shown in Fig. 1, where MMGs are composed of two microgrids MG1 and MG2. Each microgrid contain wind turbine (WT), photovoltaic (PV), diesel engine (DE), micro turbine (MT), and energy storage system (ESS) composed of batteries and loads [34].

This section establishes the mathematical model for ED of ADN with MMGs as follows.

2.1.1. Objective function for ADN

The dispatch goal of ADN is to minimize the sum of the total generation cost of units and the interaction cost with the MMGs. This objective function for ADN can be written as follows:

$$f_{\mathrm{ADN}} = f_{\mathrm{G}} + f_{\mathrm{PL}} \tag{1}$$

$$f_{\mathrm{G}} = \sum_{i=1}^{N} \left(a_i P_{\mathrm{G,i}}^2 + b_i P_{\mathrm{G,i}} + c_i + \left| \lambda_i \sin\left(\rho_i \left(P_{\mathrm{G,i}}^{\min} - P_{\mathrm{G,i}} \right) \right) \right| \right) \tag{2}$$

$$f_{\mathrm{PL}} = \sum_{j=1}^{T} c_{\mathrm{PL}} P_{\mathrm{MG,j}} \tag{3}$$

where f_{ADN} is the total production cost of the ADN; f_{G} is the generation cost of units in the ADN as formulated in (2); and f_{PL} represents the revenue that the ADN gains from supplying power flow to MMGs; a,b,c are the fuel-cost coefficients; λ and ρ are the extra fuel-cost coefficients because of valve point effect [35]; and $P_{\mathrm{G,i}}$ is the generated output of unit i; N is the total number of units; $P_{\mathrm{MG,j}}$ is the power transmitted from the distribution network to the microgrid; Trepresents the number of microgrids connected to the ADN; c_{PL} is the purchase price of electricity.

2.1.2. Constraint for ADN

$$P_{\mathrm{G}} = \sum_{j=1}^{T} P_{\mathrm{MG,j}} + P_{\mathrm{D}} \tag{4}$$

$$P_{\mathrm{G,min}} \le P_{\mathrm{G}} \le P_{\mathrm{G,max}} \tag{5}$$

where P_D represents the system loads; $P_{\mathrm{G,min}}$ and $P_{\mathrm{G,max}}$ are the lower and upper limits of the unit outputs.

If $\sum_{j=1}^{T} P_{\mathrm{MG,j}} > 0$, it means the MMGs generation is excessive and sold to ADN to make revenue; if not, the MMGs generation is insufficient and should buy power from ADN.

2.1.3. Objective function for microgrid

$$\begin{aligned}
& f_{\mathrm{MG}} = \sum_{j=1}^{N_{MG}} (f_1 + f_2 + f_3) \\
& f_1 = \sum_{w=1}^{N_{PV}} c_{\mathrm{PV}} P_{\mathrm{PV,w}} + \sum_{v=1}^{N_{WT}} c_{\mathrm{WT}} P_{\mathrm{WT,v}} + \left| \sum_{d=1}^{N_{ESS}} c_{\mathrm{ESS}} P_{\mathrm{ESS,d}} \right| \\
& f_2 = \sum_{x=1}^{N_{DE}} \left(a_x P_{\mathrm{DE,x}}^2 + b_x P_{\mathrm{DE,x}} + c_x \right) + \sum_{y=1}^{N_{MT}} c_{\mathrm{MT}} P_{\mathrm{MT,y}} \\
& f_3 = c_{\mathrm{PL}} \mathrm{P}_{\mathrm{MG,j}}
\end{aligned} \tag{6}$$

where a_x, b_x, c_x are the cost coefficients of diesel power generation, $P_{\mathrm{MT,y}}, P_{\mathrm{PV,w}}, P_{\mathrm{WT,v}}, P_{\mathrm{DE,x}}$ are the output power of MT, PV, WT and DE; c_{PV}, $c_{\mathrm{WT}}, c_{\mathrm{ESS}}, c_{\mathrm{MT}}$are the operation and maintenance cost coefficients of PV, WT, ESS, MT.

2.1.4. Constraint for microgrid

$$P_{\mathrm{ESS,d,j}} + P_{\mathrm{MG,j}} + P_{\mathrm{PV,w,j}} + P_{\mathrm{WT,v,j}} + P_{\mathrm{MT,y,j}} + \sum_{x=1}^{N_{MT}} P_{\mathrm{DE,x,j}} = P_{MGD,\mathrm{j}} \tag{7}$$

$$\begin{cases}
P_{PV,\mathrm{w,j}}^{\min} \le P_{PV,\mathrm{w,j}} \le P_{PV,\mathrm{w,j}}^{\max} \\
P_{WT,\mathrm{v,j}}^{\min} \Big/ \le P_{WT,\mathrm{v,j}} \le P_{WT,\mathrm{v,j}}^{\max} \\
P_{\mathrm{MT,y,j}}^{\min} \le P_{\mathrm{MT,y,j}} \le P_{\mathrm{MT,y,j}}^{\max} \\
P_{DE,\mathrm{x,j}}^{\min} \le P_{DE,\mathrm{x,j}} \le P_{DE,\mathrm{x,j}}^{\max} \\
P_{\mathrm{ESS,d,j}}^{\min} \le P_{\mathrm{ESS,d,j}} \le P_{\mathrm{ESS,d,j}}^{\max}
\end{cases} \tag{8}$$

where $P_{MGD,\mathrm{j}}$ represents the system load of the microgrid; $P_{PV,\mathrm{w,j}}^{\min}/P_{PV,\mathrm{w,j}}^{\max}$, $P_{WT,\mathrm{v,j}}^{\min}/P_{WT,\mathrm{v,j}}^{\max}$, $P_{\mathrm{ESS,d,j}}^{\min}/P_{\mathrm{ESS,d,j}}^{\max}$, $P_{DE,\mathrm{x,j}}^{\min}/P_{DE,\mathrm{x,j}}^{\max}$, $P_{\mathrm{MT,y,j}}^{\min}/P_{\mathrm{MT,y,j}}^{\max}$are the minimum/maximum generated output of PV, WT, ESS, DE and MT.

2.1.5. Constraint for branch flow

The branch flow model (BFM) is introduced in [36]. The following formula is used to calculate the constraint for branch flow segment:

$$\begin{cases}
\sum_{k\in\delta(j)} P_{\mathrm{jk,t}} - \sum_{i\in\pi(j)} \left(P_{\mathrm{jk,t}} - \widetilde{I}_{\mathrm{ij,t}} r_{\mathrm{ij}} \right) = P_{\mathrm{G}} - \sum_{j=1}^{T} P_{\mathrm{MG,j}} - P_{\mathrm{D}} \\
\sum_{k\in\delta(j)} Q_{\mathrm{jk,t}} - \sum_{i\in\pi(j)} \left(Q_{\mathrm{jk,t}} - \widetilde{I}_{\mathrm{ij,t}} x_{\mathrm{ij}} \right) + b_{\mathrm{j}} \widetilde{V_{\mathrm{j,t}}} = Q_{\mathrm{j,t}}^{\mathrm{G}} - Q_{\mathrm{j,t}}^{\mathrm{L}} \\
\widetilde{V_{\mathrm{j,t}}} = \widetilde{V_{\mathrm{i,t}}} - 2\left(P_{\mathrm{ij,t}} r_{\mathrm{ij}} + Q_{\mathrm{ij,t}} x_{\mathrm{ij}} \right) + \widetilde{I}_{\mathrm{ij,t}} \left(r_{\mathrm{ij}}^2 + x_{\mathrm{ij}}^2 \right) \\
\left\| \begin{matrix} 2P_{\mathrm{ij,t}} \\ 2Q_{\mathrm{ij,t}} \\ \widetilde{I}_{\mathrm{ij,t}} - \widetilde{V_{\mathrm{i,t}}} \end{matrix} \right\|_2 \le \widetilde{I}_{\mathrm{ij,t}} + \widetilde{V_{\mathrm{i,t}}}
\end{cases} \tag{9}$$

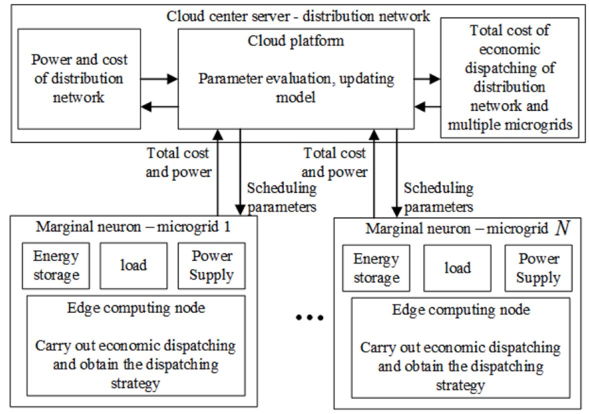

Fig. 2. Basic framework of cloud edge computing for Economic dispatch of active distribution network with multi-microgrids.

Where branch ij denotes that the positive direction of power flow is from bus i to bus j; $P_{\mathrm{ij,t}}/Q_{\mathrm{ij,t}}$ are the active/reactive power flow from bus i to bus j at time period t; $\widetilde{I}_{\mathrm{ij,t}}/\widetilde{V_{\mathrm{i,t}}}$ represents the current quadratic of branch ij and voltage quadratic of bus j at time period t; $r_{\mathrm{ij}}/x_{\mathrm{ij}}$ are the resistance/reactance of branch ij; b_{j} the shunt susceptance from bus j to ground; $\delta(j)/\pi(j)$are the set of buses whose parent/child is bus j; $Q_{\mathrm{j,t}}^{\mathrm{G}}$ represents the reactive power for unit bus j at time period t; $Q_{\mathrm{j,t}}^{\mathrm{L}}$ is the reactive load for bus j at time period t.

$$Q_{\mathrm{i,min}}^{\mathrm{G}} \le Q_{\mathrm{i,t}}^{\mathrm{G}} \le Q_{\mathrm{i,max}}^{\mathrm{G}} \tag{10}$$

Where $Q_{\mathrm{i,min}}^{\mathrm{G}}/Q_{\mathrm{i,max}}^{\mathrm{G}}$ are the lower and upper limits for reactive power of the unit.

$$\begin{cases}
V_{\mathrm{i,min}}^2 \le \widetilde{V_{\mathrm{i,t}}} \le V_{\mathrm{i,max}}^2 \\
0 \le \widetilde{I}_{\mathrm{ij,t}} \le I_{\mathrm{ij,max}}^2
\end{cases} \tag{11}$$

Where $V_{\mathrm{i,min}}/V_{\mathrm{i,max}}$ are the lower/upper bound of voltage magnitude at bus i; $I_{\mathrm{ij,max}}$ is the current capacity limit of branch ij.

2.2. Cloud edge model

The communication data between the microgrid and ADN may be leaked or attacked in the traditional centralized or distributed dispatch. To solve this problem, the cloud edge computing is used to ED of ADN with MMGs. The specific modeling process is shown in Fig. 2.

In the framework, cloud server calculates the ED of ADN, while each edge server calculates the ED of microgrid. Due to the power exchange between ADN and MMG, the ED models of ADN and MMG are coupled with each other, so ADN and MMG cannot be solved independently. To enable the cloud server and the edge servers to use multi-agent algorithms for independent optimization, the ADN and MMGs need to be decoupled. Hence, the power of the connection point between the ADN and MMGs is equivalent to a virtual load $p_{\mathrm{ADN,MG}}$ in the ADN and is equivalent to a virtual generator $p_{\mathrm{MG,ADN}}$ in the microgrid. The cloud server calculates f_G, $p_{\mathrm{ADN,MG}}$, and sends the parameters and virtual load to the edge server. Meanwhile, each edge server calculates f_{MG}, $p_{\mathrm{MG,ADN}}$ and uploads parameters to cloud server. The above process iterates repeatedly until the error is satisfied. Finally, the global optimal cost is obtained.

3. Cloud edge computing method

3.1. Basic framework

MADDPG algorithm is a promising solution to realize cloud edge computing. Since each microgrid as an agent does not need to get the

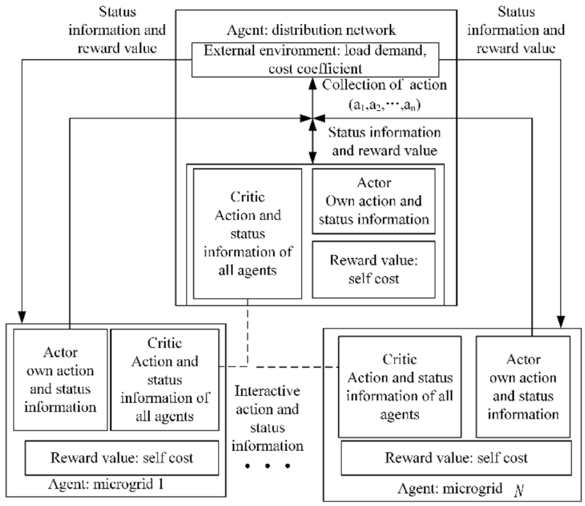

Fig. 3. Multi agent scheme for distribution network with multi-microgrids.

action information of other microgrids, the privacy is effectively protected. Moreover, the communication burden of ADN is reduced.

Based on the MADDPG, a cloud edge computing method for ADN with MMGs is proposed, as indicated in Fig. 3. In the MADDPG algorithm, the edge server acts as an e-agent, and the cloud server acts as a c-agent.

In the training stage, each agent trains its own model using local historical data. There is no need for information interaction between agents, which not only protects data privacy, but also reduces the burden of communication. In the cloud side execution stage, each e-agent exchanges only a small amount of information with c-agent (status: power of connection point and the total cost), but does not interact with other agents.

3.2. Multi agent strategy

The MADDPG algorithm has been complemented based on the traditional Actor-Critic (A-C) algorithm, allowing the critic network to collect the strategies of other agents to learn. Each e-agent and c-agent distributed computes the current state s, action value a, reward r, and next state $s^{'}$, which constitute the sequence $(s, a, r, s^{'})$ and are deposited in the experience replay buffer D. When the number of caches in D is greater than a threshold, the network starts learning. The cumulative reward expectation of each agent is expressed as follows:

$$J(\theta_i) = E_{s\sim\rho^{\pi}, a_i\sim\pi_{\theta_i}}\left[\sum_{t=0}^{\infty}\gamma^t r_i, t\right] \tag{12}$$

where p^{π} is the state assignment; t is the instant time; θ_i is the probability assignment operation of action and is implicit in policy π_i; and the function E is the expectation function; $\theta = \{\theta_1, \theta_2, ..., \theta_N\}$ represents the parameters of N agents strategy networks; $\pi = \{\pi_1, \pi_2, ..., \pi_N\}$ is denoted as the policy for N agents. The gradient strategy of MADDPG algorithm is updated as follows:

$$\begin{aligned}&\nabla_{\theta_i} J(\mu_i) = E_{x,a\sim D}\left[\nabla_{\theta_i\mu_i}(a_i|o_i)u\right]\\&u = \nabla_{a_i} Q_i^{\mu}(x, a_1, a_2, ..., a_n)\big|_{a_i=\mu_i(o_i)}\end{aligned} \tag{13}$$

where D denotes experience buffer, whose elements are $(x, x^{'}, a_1, ..., a_n, r_i, ..., r_n)$; $E_{x,a\sim D}$ is expected return; $(a_i|o_i)u$ is continuous policy parameter; $Q_i^{\mu}(x, a_1, a_2, ..., a_n)$ is centralized action value function. The update strategy of Q-value function of MADDPG algorithm is as follows:

$$\begin{aligned}&L(\theta_i) = E_{x,a,r,x^{'}}\left[\left(Q_i^{\mu}(x, a_1, a_2, ..., a_N) - y\right)^2\right]\\&\text{where} y = \left(r_i + \gamma Q_i^{\mu^{'}}\left(x^{'}, a_1^{'}, a_2^{'}, ..., a_N^{'}\right)\right)\big|_{a_i=\mu_i(o_i)}\end{aligned} \tag{14}$$

The update strategy of key target network and actor target network adopts soft update according to the following principles:

$$\theta_i^{Q^{'}} \leftarrow \tau\theta_i^{Q} + (1-\tau)\theta_i^{Q^{'}} \tag{15}$$

$$\theta_i^{\pi^{'}} \leftarrow \tau\theta_i^{\pi} + (1-\tau)\theta_i^{\pi^{'}} \tag{16}$$

where τ is the soft renewal coefficient.

3.3. Design of state, action, reward

To make the optimal ED decision with the system, each e-agent adjusts the output of its own DGs, and c-agent adjusts the output of its own units. In the period t, the environment provides the observed system state $s_t \in S$ to the agent, and the agent generates dynamic action a_l based on strategy π (strategy π is a function of Mapping state s to action a, i.e. $\pi : S \rightarrow A \Rightarrow a = \pi(s)$).

3.3.1. State space

E-agent state space: The state space is the part of environmental information perceived by the agent. The state space of each microgrid agent includes power of DGs, load power and power of virtual generators in the region, as shown in (14).

$$\begin{aligned}&s_e = \left\{P_{PV,w}, P_{WT,v}, P_{ESS,d}, P_{DE,x}, P_{MT,y}, P_{MG,ADN}, I_e, P_{MGD,j}\right\}\\&I_e = \left\{c_{PV}, c_{WT}, c_{ESS}, a_x, b_x, c_x, c_{MT}, c_{PL}, \phi_j, \varepsilon_2\right\}\end{aligned} \tag{17}$$

C-agent state space: The state space of c-agent includes the power of thermal generators and the power of virtual loads in the region, as shown in (15).

$$\begin{aligned}&s_c = \left\{P_{G,i}, P_{ADN,MG}, I_e, P_D\right\}\\&I_e = \left\{a_i, b_i, c_i, \lambda_i, \rho_i, c_{PL}, \phi_j\right\}\end{aligned} \tag{18}$$

To judge whether the error of the $p_{MG,ADN}$ and the $p_{ADN,MG}$ is within range, c-agent sends the power of virtual load to e-agent, and e-agent uploads the power of virtual generator, as shown in (16).

$$\left|p_{MG,ADN} - p_{ADN,MG}\right| \le \varepsilon_2 \tag{19}$$

It can be seen that the $p_{MG,ADN}$ and the $p_{ADN,MG}$ should be close enough to meet the requirement of the error range.

3.3.2. Action space

E-agent action space: Relevant decision variables as action space. The action space of each regional e-agent is the output change of the controllable equipment in its control region, as shown in (17).

$$a_e = \left\{\Delta P_{PV,w}, \Delta P_{WT,v}, \Delta P_{ESS,d}, \Delta P_{DE,x}, \Delta P_{MT,y}, \Delta p_{MG,ADN}\right\} \tag{20}$$

C-agent action: The action space is the change in the power of the thermal generator and the power change of the virtual load in its control region, as shown in (18).

$$a_c = \left\{\Delta P_{G,i}, \Delta P_{ADN,MG}\right\} \tag{21}$$

3.3.3. Reward

Reward space: While optimizing objective cost of the ADN and microgrid, the $p_{MG,ADN}$ and the $p_{ADN,MG}$ must is coordinated. Thus, the penalty function is proposed to add to the objective function of the microgrid to describe the deviation of the $p_{MG,ADN}$ and the $p_{ADN,MG}$, as shown in (19).

$$\min f_{MG} + \phi_{MG}\left|p_{MG,ADN} - p_{ADN,MG}\right| \tag{22}$$

where ϕ_j is the multiplier of penalty function.

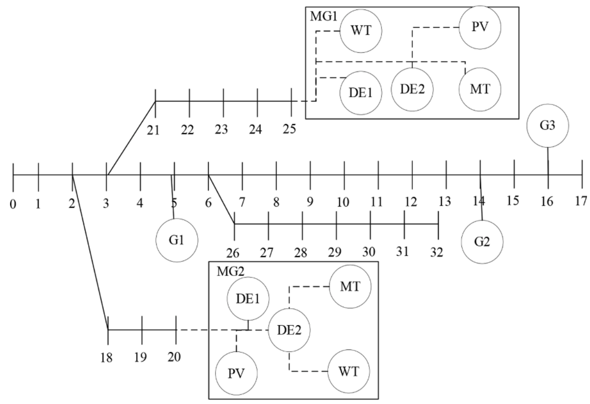

Fig. 4. IEEE33 node system.

Similarly, if T microgrids are connected to the ADN, then the penalty functions can be added to the objective function of the ADN to describe the deviation of $p_{\mathrm{MG,ADN}}$ and $p_{\mathrm{ADN,MG}}$, as shown in (20).

$$\min f_G + \sum_{j=1}^{T} \phi_{\mathrm{ADN}} \left| p_{\mathrm{MG,ADN}} - p_{\mathrm{ADN,MG}} \right| \tag{23}$$

The reward value of each agent is the negative value of its own cost, as shown in (21).

$$r_t(s_t, a_t) = -f(s_t, a_t) \tag{24}$$

where, the c-agent is f_G and the e-agent is f_{MG}.

The overall dispatch is optimal when the reward values of all agents is converged.

4. Case study

In this section, there are two case studies to verify the reliability of the proposed cloud edge computing method. The first case studies the effectiveness of the method with data privacy protection. The second case takes a larger ADN as an example to further verify the effectiveness of the method, in addition to reduces the communication burden. The proposed MADDPG is compared with the DDPG, which has been the most popular RL-based methods over the last five years. Python is selected as the programming language.

4.1. IEEE33 node system

The active distribution network structure adopts IEEE 33 node system in Fig. 4, in which MG1 and MG2 are connected to the ADN at 20th node and 25th node respectively. The load demand of distribution network is 4.1MW, the load demand of MG1 is 3.6MW and the load demand of MG2 is 3.4MW. The parameters of each unit in the ADN are listed in Table 1, the diesel engine parameters are listed in Table 2, and the operation and maintenance cost of each distributed power are listed in Table 3.

4.1.1. Convergence analysis

The implementation details of the proposed MADDPG algorithm are as follows. In the training stage, there are 100 episodes, each of which contains ten days, and each day contains 24-time slots. This paper collects off-line data sets to train the optimal ED strategy of local agent. In each actor network, we exploit four fully connected layers, where there are 1024, 2048, 512, and 128 nodes in each layer. Each critic network includes five fully connected layers, having 512, 1024, 2048, 512, and 128 neurons, respectively. The learning results are updated to the global network regularly. There are many random choices at the beginning of learning. However, the ED chooses the action of optimization goal through multiple iterations. The sum of the rewards for the MADDPG algorithm methods are given in Fig. 5. The output result and the cost of the equipment are presented in Fig. 6.

The rewards value in Fig. 5 is the system's total rewards after convergence of the training model, including the sum of the rewards of all e-agents and c-agent. Since the exploration direction has randomness at the initial stage of training, the reward value of the system is relatively low and has no obvious upward or downward trend. However, the reward value has an obvious upward trend with the increase of episode. After 50 episodes of learning, the reward value reaches the maximum and tends to be stable. This result reflects that the MADDPG algorithm has accumulated some experience in the learning process, which is

Table 2
Parameters of diesel engine unit.

Region	Unit	a (\$/kW^{2}h)	b(\$/kWh)	c(\$/h)	$P^{\min}$(kW)	$P^{\max}$(kW)
MG1	DE1	0.0003	0.30	40	0	1500
	DE2	0.0005	0.21	30	100	1500
MG2	DE1	0.0004	0.27	70	100	1500
	DE2	0.0006	0.18	32	0	1500

Table 3
Capacity configuration and running cost coefficient of each distributed power.

Region	Equipment	$P^{\min}$(kW)	$P^{\max}$(kW)	Operation and maintenance cost (\$/kW)
MG1	PV1	0	155	0.025
	WT1	0	135	0.024
	ESS1	−35	35	0.065
	MT1	0	300	0.058
MG2	PV2	0	170	0.03
	WT2	0	120	0.032
	ESS2	−35	35	0.065
	MT2	0	345	0.056

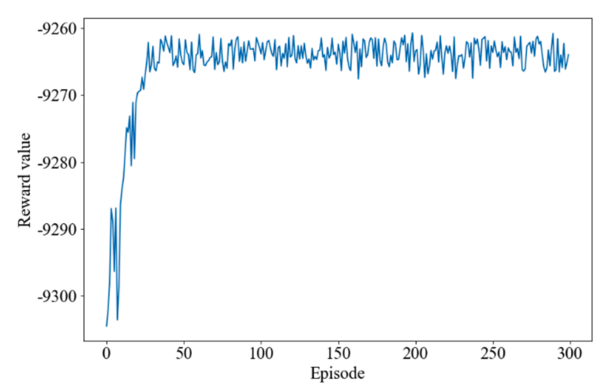

Fig. 5. Change curve of reward value in MADDPG learning process.

Table 1
Parameters of each unit of ADN.

Unit	a (\$/kW^{2}h)	b(\$/kWh)	c(\$/h)	λ(\$/h)	ρ(\$/kWh)	$P^{\min}$(kW)	$P^{\max}$(kW)
G1	0.0004	0.25	40	300	0.035	200	2000
G2	0.0006	0.2	40	200	0.042	100	1500
G3	0.0008	0.15	30	200	0.042	0	1500

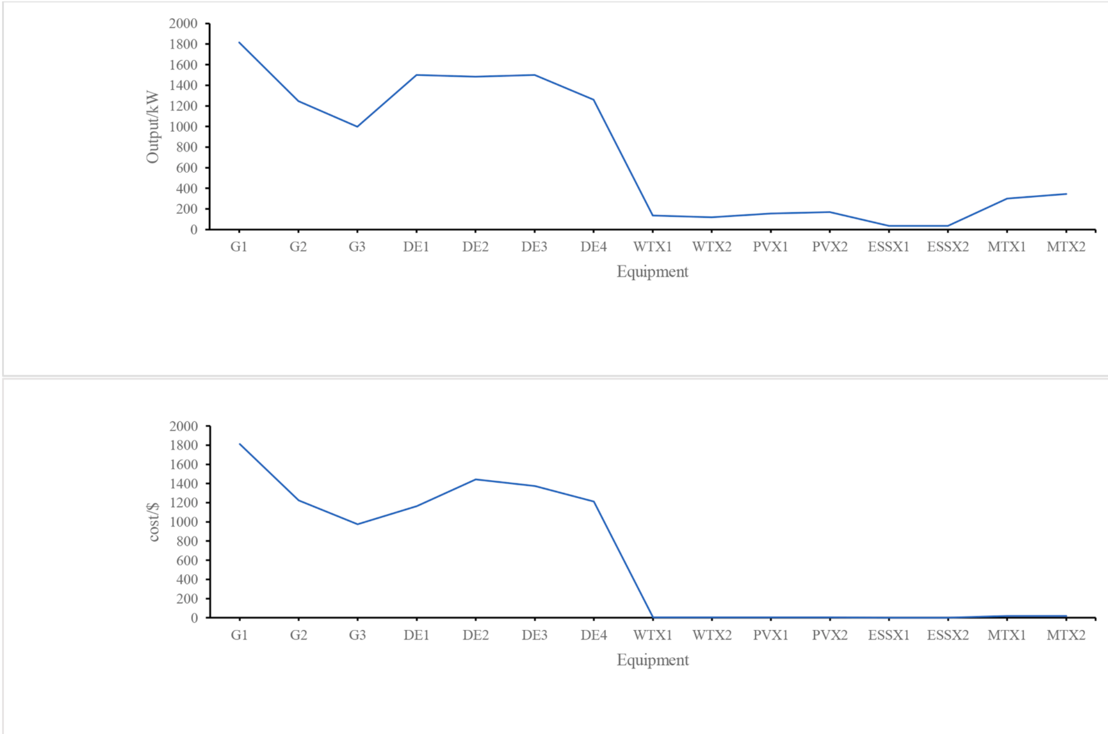

Fig. 6. The output result and the cost of the equipment.

Table 4
Equipment output and cost.

Region	Equipment	Output (kW)	Cost ($)
ADN	G1	1815.677816	1812.597
	G2	1247.198247	1222.744
	G3	997.5986976	975.8036
MG1	DE1	1500	1165
	DE2	1483.381483	1441.718
	WTX1	1500	1375
	PVX1	1261.151261	1213.307
	ESSX1	135	3.24
	MTX1	120	3.84
MG2	DE3	155	3.875
	DE4	170	5.1
	WTX2	35	2.275
	PVX2	35	2.275
	ESSX2	300	17.4
	MTX2	345	19.32

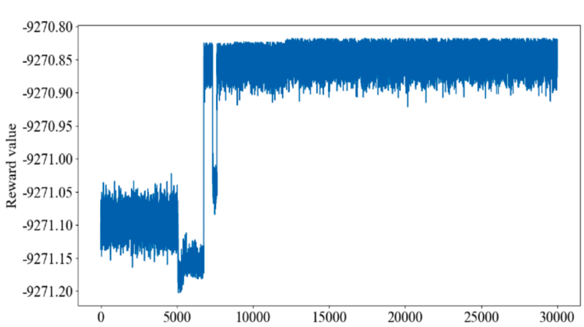

Fig. 7. Reward value change curve of DDPG during learning.

enough to make reasonable decisions in ADN with MMGs. The specific data of equipment output results and costs are listed in Table 4. This result reflects that the interaction between ADN and Microgrids can be completed without leaking data privacy based on cloud edge computing.

Table 5
Equipment output and cost.

Method	Minimum cost($/h)	Average cost($/h)	Maximum cost($/h)
DDPG	9270.75	9270.975	9271.2
MADDPG	9263.4946	9263.6423	9263.79

4.1.2. Result analysis

As the comparison scheme, the conventional single-agent DDPG algorithm dispatch strategy is set to verify the advantages of the MADDPG algorithm proposed in this paper. Optimal energy management of multi-microgrids connected to distribution system based on DDPG is introduced in [10]. The DDPG algorithm has only one agent, which gathers the power of all equipment. The reward value of DDPG algorithm is given in Fig. 7.

DDPG algorithm sampled the same data as the MADDPG algorithm. After 30,000 episodes, the model can generate the best action. Comparing the two schemes, the time of DDPG takes longer than the time of MADDPG. In DDPG algorithm, all computations are performed in the same agent, which leads to a longer time to explore the environment. From Table 5, the average generation operation cost of the ADN with

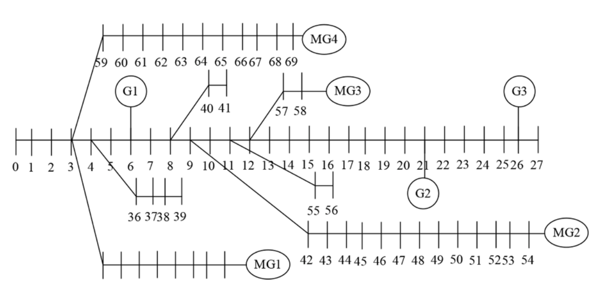

Fig. 8. IEEE69 node system.

Table 6
Parameters of diesel engine unit.

Region	Unit	a (\$/kW^{2}h)	b(\$/kWh)	c(\$/h)	P^{min}(kW)	P^{max}(kW)
MG3	DE1	0.0003	0.28	39	100	1500
	DE2	0.0004	0.23	31	100	1500
MG4	DE1	0.0005	0.26	72	100	1500
	DE2	0.0007	0.19	33	90	1500

Table 7
Capacity configuration and operation cost coefficient of each distributed power.

Region	Equipment	P^{min}(kW)	P^{max}(kW)	Operation and maintenance cost (\$)
MG3	PV3	0	200	0.089
	WT3	0	300	0.102
	ESS3	-60	60	0.032
	MT3	0	350	0.057
MG4	PV4	0	300	0.035
	WT4	0	200	0.098
	ESS4	-60	60	0.034
	MT4	0	360	0.059

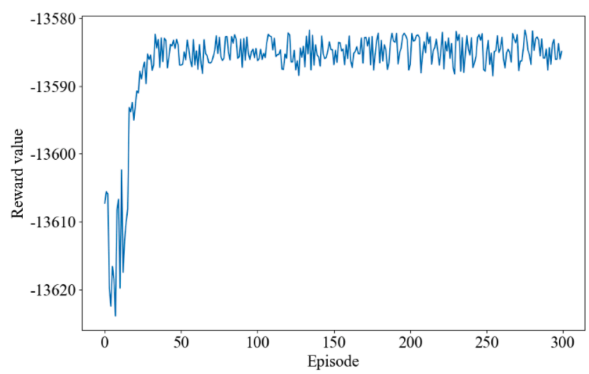

Fig. 9. Reward value change curve of MADDPG during learning.

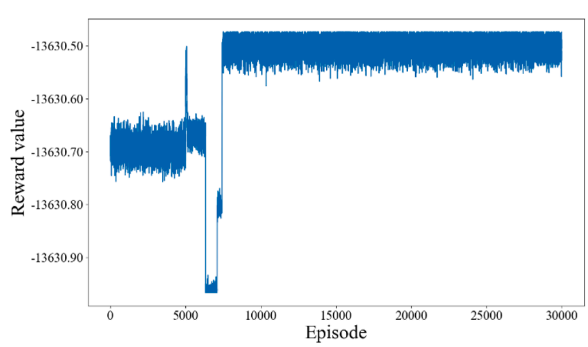

Fig. 10. Reward value change curve of DDPG during learning.

MMGs is 9263.6423\$/h by the MADDPG algorithm, and 9270.975 \$/h by the DDPG algorithm. The evaluation results illustrate the one-agent DDPG algorithm are not suitable for the ADN containing multiple microgrids.

4.2. IEEE69 node system

In Fig. 8, IEEE 69 node distribution system is selected as a supplementary example to further verify the reliability of the method. The total load demand is 18 mW. The parameters of each unit at the ADN are listed in Table 1. The relevant parameters of MG1 and MG2 are listed in Table 2 and Table 3. The relevant parameters of MG3 and MG4 are listed in Table 6 and Table 7.

Table 8
Output of different methods.

Region	Output	Power of DDPG (kW)	Power of LINGO (kW)	Power of MADDPG (kW)
ADN	G1	1726.779	1725.916	1725.917
	G2	1172.984	1172.398	1172.399
	G3	923.2593	922.7979	922.7984
MG1	DE1	1507.5	1500	1500.001
	DE2	1434.821	1427.683	1427.684
	WT	135	135	135
	PV	155	155	155
	ESS	35	35	35
	MT	300	300	300
MG2	DE1	1500	1500	1500
	DE2	1221.426	1215.349	1215.35
	WT	120	120	120
	PV	170	170	170
	ESS	35	35	35
	MT	345	345	345
MG3	DE1	1500	1500	1500
	DE2	1500	1500	1500
	WT	300	300	300
	PV	200	200	200
	ESS	60	60	60
	MT	350	350	350
MG4	DE1	1385.337	1378.445	1378.446
	DE2	1037.573	1032.411	1032.412
	WT	200	200	200
	PV	300	300	300
	ESS	60	60	60
	MT	360	360	360

Table 9
Cost and time of different methods.

	DDPG	LINGO	MADDPG
Total cost(\$)	13,616.31	13,584.4674	13,584.47162
Time(s)	30.54	15.24	15.34

4.2.1. Convergence analysis

This case aims to verify that the communication burden of the method is reduced based on protecting the data privacy. The simulation results of DDPG algorithm and the simulation results of MADDPG algorithm are compared inFig. 9.

The ADN becomes larger in Figs. 9 and 10. The change curve of reward for MADDPG algorithm is not affected. In contrast, the curve of reward for DDPG algorithm fluctuated continuously during the training process. This result reflects that the change of power grid increases the communication burden with the conventional algorithm.

4.2.2. Comparison of result

In order to further illustrate that the method proposed in this paper is effective in the ADN with MMGs, in addition to comparing with the DDPG algorithm, it is also compared with Lingo tool. The comparison results of output are listed in Table 8. The total cost and time are listed in Table 9.

As shown in Table 8 and Table 9, the output cost of DDPG algorithm is 13,616.31\$, the output cost of MADDPG algorithm is 13,584.45162\$. the output cost of DDPG algorithm is higher than the output cost of MADDPG algorithm based on the same load and parameters. The cost of MADDPG algorithm is basically consistent with the optimal cost of LINGO. This result reflects that the MADDPG algorithm performs much better than the traditional algorithm. Due to the microgrid's data of DDPG algorithm is calculated in the cloud server, but the microgrid's data of MADDPG algorithm is calculated at its own edge server, the dispatch decision of DDPG algorithm takes a longer time than the dispatch decision of MADDPG algorithm. The evaluation results illustrate the MADDPG algorithm effectively prevents the privacy problem of data transmission, in addition to reduces the communication burden.

5. Conclusion

Aiming at the problem that the risks and challenges of privacy data leakage and the communication burdens in the traditional economic dispatch, a cloud edge computing method for ED of ADN with MMGs is proposed. Cloud server computes ED of ADN. Each edge server computes ED of each microgrid. The MADRL is employed to realize cloud edge computing. The training stage in MADRL is improved. each agent trains its own model using local historical data. There is no need for information interaction between agents, which not only protects data privacy, but also reduces the burden of communication. As an agent, each edge server and cloud server make decisions quickly. Then the overall optimal cost is computed. In the case study, based on optimized quality unchanged, the data privacy of the microgrids and the ADN is protected in the whole process. While the overall objective optimization is meet, the communication burdens is reduced.

CRediT authorship contribution statement

Xueping Li: Conceptualization, Methodology, Software. **Jie Wang:** Investigation, Data curation, Writing – original draft. **Zhigang Lu:** Supervision. **Yao Cai:** Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

Acknowledgements

The authors are very grateful to the helpful comments from the editors and reviewers which significantly improved the quality of this paper. This work is supported in part by National Natural Science Foundation of China (No. 61473246) and Natural Science Foundation of Hebei Province (No. E2021203004).

References

[1] R. Zamora, A.K. Srivastava, Controls for microgrids with storage: review, challenges, and research needs, Renew. Sustain. Energy Rev. 14 (7) (Sep 2010) 2009–2018.
[2] L. Li, Q.S. Xu, X.X. Huo, B.G. Zhao, Ieee, Day-ahead centralized optimal dispatching of active distribution power system with combined cooling, heating and power-based microgrids, in: 8th IEEE Annual International Conference on Cyber Technology in Automation, Control, and Intelligent Systems (IEEE-CYBER), Tianjin, PEOPLES R CHINA, 2018, pp. 1300–1304, 2018.
[3] Z.H. Bie, P. Zhang, G.F. Li, B.W. Hua, M. Meehan, X.F. Wang, Reliability evaluation of active distribution systems including microgrids, IEEE Trans. Power Syst. 27 (4) (Nov 2012) 2342–2350.
[4] D. Celik, M.E. Meral, Multi-objective control scheme for operation of parallel inverter-based microgrids during asymmetrical grid faults, IET Renew. Power Gener. 14 (13) (Oct 2020) 2487–2498.
[5] D. Celik, M.E. Meral, A coordinated virtual impedance control scheme for three phase four leg inverters of electric vehicle to grid (V2G), Energy 246 (May 2022). Art. no. 123354.
[6] Y. Li, et al., Optimal scheduling of isolated microgrid with an electric vehicle battery swapping station in multi-stakeholder scenarios: a bi-level programming approach via real-time pricing, Appl. Energy 232 (Dec 2018) 54–68.
[7] T.L. Vandoorn, B. Renders, L. Degroote, B. Meersman, L. Vandevelde, Active load control in islanded microgrids based on the grid voltage, IEEE Trans. Smart Grid 2 (1) (Mar 2011) 139–151.
[8] H.B. Sun, B.M. Zhang, W.C. Wu, Q.L. Guo, Ieee, Family of energy management system for smart grid, in: 3rd IEEE PES International Conference and Exhibition on Innovative Smart Grid Technologies Europe (ISGT Europe), Berlin, GERMANY, Tech Univ Berlin, 2012, p. 2012.
[9] Z.R. Xu, P. Yang, C.L. Zheng, Y.J. Zhang, J.J. Peng, Z.J. Zeng, Analysis on the organization and Development of multi-microgrids, Renew. Sustain. Energy Rev. 81 (Jan 2018) 2204–2216.
[10] M. Xie, X. Ji, X.T. Hu, P.J. Cheng, Y.X. Du, M.B. Liu, Autonomous optimized economic dispatch of active distribution system with multi-microgrids, Energy 153 (Jun 2018) 479–489.
[11] C.Y. Guo, X. Wang, Y.H. Zheng, F. Zhang, Optimal energy management of multi-microgrids connected to distribution system based on deep reinforcement learning, Int. J. Electr. Power Energy Syst. 131 (Oct 2021). Art. no. 107048.
[12] G. Chen, J.H. Ren, E.N. Feng, Distributed finite-time economic dispatch of a network of energy resources, IEEE Trans. Smart Grid 8 (2) (Mar 2017) 822–832.
[13] M. Mohiti, H. Monsef, A. Anvari-moghaddam, J. Guerrero, H. Lesani, A decentralized robust model for optimal operation of distribution companies with private microgrids, Int. J. Electr. Power Energy Syst. 106 (Mar 2019) 105–123.
[14] J.R. Zhang, X.Q. Zhu, T.P. Chen, Y.L. Yu, W.D. Xue, Improved MOEA/D approach to many-objective day-ahead scheduling with consideration of adjustable outputs of renewable units and load reduction in active distribution networks, Energy 210 (Nov 2020). Art. no. 118524.
[15] H.M. Cai, B.Y. Xu, L.H. Jiang, A.V. Vasilakos, IoT-based big data storage systems in cloud computing: perspectives and challenges, IEEE Internet Things J. 4 (1) (Feb 2017) 75–87.
[16] Y. Yu, R.N. Chen, H.L. Li, Y.N. Li, A.K. Tian, Toward data security in edge intelligent IIoT, IEEE Netw. 33 (5) (Sep-Oct 2019) 20–26.
[17] J. Ren, D.Y. Zhang, S.W. He, Y.X. Zhang, T. Li, A survey on end-edge-cloud orchestrated network computing paradigms: transparent computing, mobile edge computing, fog computing, and cloudlet, ACM Comput. Surv. 52 (6) (Jan 2020). Art. no. 125.
[18] S.Y. Wang, X.D. Wang, W.C. Wu, Cloud computing and local chip-based dynamic economic dispatch for microgrids, IEEE Trans. Smart Grid 11 (5) (Sept 2020) 3774–3784.
[19] D.W. Fang, X. Guan, L. Lin, Y. Peng, D. Sun, M.M. Hassan, Edge intelligence based economic dispatch for virtual power plant in 5G internet of energy, Comput. Commun. 151 (Feb 2020) 42–50.
[20] F. Ma, X.C. Luo, E. Litvinov, Cloud computing for power system simulations at ISO New England-experiences and challenges, IEEE Trans. Smart Grid 7 (6) (Nov 2016) 2596–2603.
[21] W. Dong, Q. Yang, W. Li, A.Y. Zomaya, Machine-learning-based real-time economic dispatch in islanding microgrids in a cloud-edge computing environment, IEEE Internet Things J. 8 (17) (Sept 2021) 13703–13711.
[22] L. Shen, X.B. Dou, H. Long, C. Li, J. Zhou, K. Chen, A cloud-edge cooperative dispatching method for distribution networks considering photovoltaic generation uncertainty, J. Modern Power Syst. Clean Energy 9 (5) (Sep 2021) 1111–1120.
[23] B. Li, D. Yu, J. Wu, P. Ju, Z. Li, Coordinated cloud-edge anomaly identification for active distribution networks, IEEE Trans. Cloud Comput. (2022), 1-1.
[24] Z.J. Zhang, Y.D. Zhang, D. Yue, C.X. Dou, X.H. Ding, H.F. Zhang, Economic-driven hierarchical voltage regulation of incremental distribution networks: a cloud-edge collaboration based perspective, IEEE Trans. Ind. Inf. 18 (3) (Mar 2022) 1746–1757.
[25] Y.L. Zhou, J.R. Zhang, Three-layer day-ahead scheduling for active distribution network by considering multiple stakeholders, in: Energy, 207, Sep 2020. Art. no. 118263.
[26] B. Kim, J. Park, S. Park, S. Kang, Impedance learning for robotic contact tasks using natural actor-critic algorithm, IEEE Trans. Syst. Man Cybern. Part B-Cybernetics 40 (2) (Apr 2010) 433–443.
[27] K Wan, D Wu, B Li, et al., ME-MADDPG, An efficient learning-based motion planning method for multiple agents in complex environments[J], International Journal of Intelligent Systems 37 (3) (2022) 2393–2427.
[28] L. Busoniu, R. Babuska, B. De Schutter, A comprehensive survey of multiagent reinforcement learning, IEEE Trans. Syst. Man Cybern. Part C-Appl. Rev. 38 (2) (Mar 2008) 156–172.
[29] Z.M. Yan, Y. Xu, Data-driven load frequency control for stochastic power systems: a deep reinforcement learning method with continuous action search, IEEE Trans. Power Syst. 34 (2) (Mar 2019) 1653–1656.
[30] W. Du, S.F. Ding, A survey on multi-agent deep reinforcement learning: from the perspective of challenges and applications, Artif. Intell. Rev. 54 (5) (Jun 2021) 3215–3238.
[31] L. Wang, K.Z. Wang, C.H. Pan, W. Xu, N. Aslam, L. Hanzo, Multi-agent deep reinforcement learning-based trajectory planning for multi-UAV assisted mobile edge computing, IEEE Trans. Cogn. Commun. Netw. 7 (1) (Mar 2021) 73–84.
[32] X. Chen, G.Z. Liu, Energy-efficient task offloading and resource allocation via deep reinforcement learning for augmented reality in mobile edge networks, IEEE Internet Things J. 8 (13) (Jul 2021) 10843–10856.
[33] W.X. Lei, H. Wen, J.S. Wu, W.J. Hou, MADDPG-based security situational awareness for smart grid with intelligent edge, Appl. Sci.-Basel 11 (7) (Apr 2021). Art. no. 3101.

[34] B.K. Sovacool, Deploying off-grid technology to eradicate energy poverty, Science 338 (6103) (Oct 2012) 47–48.
[35] T. Niknam, H.D. Mojarrad, H.Z. Meymand, Non-smooth economic dispatch computation by fuzzy and self adaptive particle swarm optimization, Appl. Soft Comput. 11 (2) (Mar 2011) 2805–2817.
[36] H.J. Gao, J.Y. Liu, L.F. Wang, Robust coordinated optimization of active and reactive power in active distribution systems, IEEE Trans. Smart Grid 9 (5) (Sep 2018) 4436–4447.