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Emergency Load Shedding Strategy for Microgrids Based on Dueling Deep Q-Learning

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ABSTRACT The rapid drop of frequency under the disturbance is a major threat to the safe and stable operation of a microgrid (MG) system. Emergency load shedding is the main measure to prevent continuous frequency drop and power outage. The existing load shedding strategies have poor adaptability to deal with the problem of MG load shedding under different disturbance situations, and it is difficult to ensure the safe and stable operation of an MG in different operating environments. To address this problem, this paper proposes a data-driven load shedding strategy. First, considering the importance of the load and the frequency recovery time of the system, a load shedding contribution indicator is designed that takes into account the load frequency adjustment effect and the load shedding priority. This contribution indicator is introduced as a load shedding criterion into the reward value function of dueling deep Q learning. Second, considering the suddenness and uncertainty of emergency load shedding, a MG emergency load shedding strategy (ELSS) based on dueling deep Q-learning is proposed. On this basis, the dueling deep Q learning algorithm is used to obtain the load shedding decision with the maximum cumulative reward. Finally, taking the MG load shedding cases in two different scenarios as examples, a simulation study is carried out on a modified IEEE-25 bus MG. The simulation results show that, compared with the model-driven implicit enumeration strategy (IES), the proposed ELSS has superiority in maintaining stable power supply for important loads and reducing load shedding decision-making time and frequency fluctuations.

INDEX TERMS Microgrid, emergency load shedding, deep Q-learning, frequency adjustment effect, frequency recovery.

I. INTRODUCTION

With the continuous development of the social economy, people pay more and more attention to environmental protection [1]–[3]. Clean energy generation, represented by distributed generations (DGs), has become an important direction of power grid development in the future [4]–[6]. To avoid the fluctuation and randomness of DGs directly connected to the power grid, the concept of microgrids (MGs) came into being. An MG is a small energy management system. During the grid-connected operation, the MG can effectively stabilize and control the fluctuation of DGs and reduce the impact on the distribution network. When the distribution network fails, the MG passively transfers to the islanded operation [7]. Due to the low inertia of MGs and the randomness of DGs, when the MG passively transfers to the islanded operation, there are scenarios where the power generation cannot meet the load demand. This can lead to a rapid drop in frequency in the system and even the MG power outage. To prevent serious consequences of the MG, an effective frequency control strategy is necessary to maintain system security [8], [9].

At present, load shedding is widely used as the main measure to restore system frequency. In [10], a under frequency load shedding strategy considering the uncertainty of system parameters was proposed to restore the system frequency. In [11], a two-unit wide-area adaptive load shedding scheme based on synchrophasors was proposed, which allocates the load shedding to different loads to achieve system power balance. In [12], an improved under-frequency load shedding

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scheme was proposed, which uses equivalent inertia constant to detect the power unbalance of the system. The load shedding strategy based on the system equivalent inertia constant that calculates the system power shortage mostly takes the large power grid as the load shedding research object. However, various power parameters in the MG are different, and the power generation of new energy has volatility. As a result, the control effect of the above strategies could be affected. In [13], the calculation method of load shedding is improved, and a new centralized adaptive under frequency load shedding scheme is proposed to improve the frequency stability of an islanded MG. In [14], a two-level hierarchical load shedding strategy based on decentralized methods was proposed to recovery MG frequency. In [15], a load shedding strategy considering speed and smoothness was proposed, which made up for the power shortage during the unintentional islanding period of the MG. In [16], a centralized load shedding method for the islanded MG power balance was proposed, which uses nonlinear model predictive control to automatically remove non critical loads. A hierarchical load shedding strategy based on undervoltage and underfrequency is proposed in [17], which considers the priority of load shedding. In [18], a two-step load shedding method is proposed, which avoids the rapid frequency deviation in the first step. The second step is to shed the load according to the importance of the load. It can be observed from the literature survey that the above research only considered the importance of load to guide the level of load shedding.

In [19], an effort-based load shedding method was proposed for an MG. This method uses the effort index to allocate the load shedding of each MG. A coordinated load shedding strategy based on four-dimensional analysis is proposed in [20]. This strategy uses a 4-D piecewise linear curve to adaptively specify the load shedding amount. In [21], a hierarchical load shedding strategy was proposed. This strategy can eliminate the voltage and frequency deviations in the load shedding through a centralized secondary controller. In [22], a pre-emptive load shedding strategy was proposed. This strategy can shorten the system frequency recovery time. In [23], an adaptive load shedding algorithm including the battery support was proposed to achieve the system frequency stability. The above methods can be classified as model-based methods, which describe the load shedding decision of the islanded MG by establishing mathematical equations. However, the physical model has poor adaptability to deal with the problem of MG load shedding under different disturbance situations, and it is difficult to ensure the safe and stable operation of an MG in different operating environments.

Considering the shortcomings in current load shedding strategies, the deep Q-learning algorithm based on a data-driven approach is considered a promising alternative to the load shedding strategy due to its great flexibility [24]. At present, deep Q learning is widely used in the MG operation control. A power management method based on adaptive reinforcement learning is proposed in [25]. In [26], a distributed operation method using double deep Q-learning is proposed to manage the energy storage system in the MG. These papers formulate the MG operation control as a Markov decision process (MDP) and use deep Q learning algorithms to make complex decisions that adapt to specific constraints. To overcome the problem that the deep Q learning algorithm overestimates the Q-value of action, a dueling deep Q network (DQN) structure is designed in [27], which is an improvement of the DQN in deep Q learning and can effectively solve the overestimation problem of the DQN value function. However, the application of dueling deep Q learning in the MG emergency load shedding still faces the following problems: (i) the MG operation state is complex, how to deal with the complex island MG environmental information. (ii) how to ensure stable power supply for high priority loads in the islanded MG during emergency load shedding.

To solve the above two problems faced by dueling deep Q learning in the load shedding strategy of an MG [28], this paper proposes an MG emergency load shedding strategy based on dueling deep Q learning. This paper uses the system observable state as the data sample. First, the observable and adjustable variables are selected, and the reward value is determined according to the islanded MG load shedding requirements. Then, the state action value function of an islanded MG and the Q function of DDQN are defined. The ε-greedy strategy and gradient descent method are introduced to train the neural network. Finally, the trained neural network is used to select the action with the largest estimation under each current state, and the load shedding control of islanded MG based on dueling deep Q-learning is carried out to converge the optimal load shedding decision. At the same time, the dueling deep Q-learning MG emergency load shedding strategy proposed in this paper comprehensively considers the load shedding priority and the load frequency adjustment effect and uses it for comprehensive load evaluation to ensure the stable power supply of important loads during the emergency islanding period.

The main contributions of this paper are as follows:

1) This paper proposes an emergency islanded MG load shedding strategy based on the dueling deep Q-learning. This strategy is a new type of data-driven load shedding strategy. The optimal load shedding decision is obtained through continuous interaction between agents and the environment.
2) In this paper, a load shedding contribution indicator considering the load frequency adjustment effect and load shedding priority is designed as the load shedding criterion. The load shedding criterion is introduced into the reward function setting of the ELSS based on the dueling deep Q-learning. The indicator can ensure the stable operation of important loads and shorten the frequency recovery time.
3) The emergency load shedding problem for the islanded microgrid is formulated as an MDP, which allows the consideration of the maximum accumulative reward of the load shedding decision.

The remainder of the paper is organized as follows. Section II describes the problem formulation. Section III describes the emergency load shedding criteria. The MG emergency load shedding strategy based on a dueling deep Q learning is described in Section IV. The case study in Section V illustrates the advantages of the proposed emergency load shedding strategy. Section VI concludes this paper.

II. PROBLEM FORMULATION

This paper formulates emergency load shedding from the perspective of recovering islanded MG frequency. Emergency load shedding control can regulate the load in time to restore the frequency of the islanded MG. In addition, this paper focuses on how to ensure the continuous power supply of high priority load.

To maximize the long-term reward for the emergency load shedding strategy while accounting for the stable power supply under high priority load, we recruit the MDP [29]. MDP model provides a systematic framework and decision making in a complex environment. An MDP is defined as $<$ S, A, T, R $>$, where S is the system's state space, A is the action space, T is the state transition and R is the reward function. The details about the MDP formulation are shown as follows.

A. STATE

The states are the observable variables that relate to learning efficiency and generalization. The situation that the DGs cannot meet the load demand can cause the system frequency to drop. At this time, two main variables reflecting the amount of the load shedding are the frequency and RoCoF. The RoCoF becomes zero when the power is rebalanced after the corresponding load is removed after the frequency drops. The objective of emergency load shedding is to restore the system frequency to normal range. Therefore, the RoCoF and frequency are selected as the environmental state factors.

In this section, RoCoF and frequency are divided into different intervals to correspond to different coordinate values. At the same time, the two-dimensional vector composed of RoCoF and frequency is used as the environmental state of an islanded MG.

For the frequency, the normal frequency range is set as 49.8-50 Hz. Among them, $(-\infty, 48)$ Hz corresponds to the coordinate -5; $[48, 48.5)$ Hz corresponds to the coordinate -4; $[48.5, 49)$ Hz corresponds to the coordinate -3; $[49, 49.5)$ Hz corresponds to the coordinate -2; $[49.5, 49.8)$ Hz corresponds to the coordinate -1; $[49.8, 50.2]$ Hz corresponds to the coordinate 0. The state with coordinate 0 represents that the system frequency has recovered to a safe interval. The set of states obtained from frequency f is $\{-5, -4, -3, -2, -1, 0\}$.

For the RoCoF, the larger the system RoCoF, the more serious the power shortage, which corresponds to more loads will be removed. During the frequency recovery, if the frequency is low, the frequency should be restored as soon as possible. Based on this, the RoCoF is divided into 5 intervals in this paper. $(-\infty, -4)$ Hz/s corresponds to the coordinate -4; $[-4, -3)$ Hz/s corresponds to the coordinate -3; $[-3, -2)$ Hz/s corresponds to the coordinate -2; $[-2, -1)$ Hz/s corresponds to the coordinate -1; $[-1, 0]$ Hz/s corresponds to the coordinate 0. The state with coordinate 0 represents that the system frequency recovers to a stable state. The set obtained by the RoCoF is $\{-4, -3, -2, -1, 0\}$. Combined with the six intervals corresponding to the frequency, there are 30 environmental states. A two-dimensional vector formed by two variables is regarded as the environmental state S, which is expressed as: $S = \left\{S_{ij} \in S \,|\, i \in \{-5, -4, -3, -2, -1, 0\}, j \in \{-4, -3, -2, -1, 0\}\right\}$

B. ACTION

The actions are the adjustable variables. The action set in the dueling deep Q-learning is all the action sets that can make the agent closer to the target. When the islanded MG needs the load shedding under the disturbance condition, the action set is the load removed in the system. In this paper, the load to be removed in the islanded MG is defined as load shedding action a_t. The load shedding action set A can be expressed as $A : \{a_1, a_2, \cdots, a_n\}$.

C. REWARD FUNCTION

The reward function is an important part to evaluate the action value, which reflects the influence of load shedding on the safety and reliability of the islanded MG. The goal of the load shedding strategy based on dueling deep Q-learning is to obtain the optimal load shedding decision to meet the fast frequency recovery of the islanded MG. It can provide feedback for each attempt and error learning action, and update the accumulated rewards in time.

The load shedding contribution indicator is set as a reward value function, and the quality of the load shedding strategy is defined by the reward value function. The reward function $R(s_t, s_{t+1}, a)$ is expressed as follows:

$$R(s_t, s_{t+1}, a) = \begin{cases} -1 & \text{S}=\{0, 0\} \\ W_i = L_i(\lambda_1 C_1 + \lambda_2 C_2) & \text{S} \neq \{0, 0\} \end{cases} \quad (1)$$

III. EMERGENCY LOAD SHEDDING CRITERIA

When the MG disturbance leads to the active power shortage, whether the safe and stable operation of the system can be restored quickly and stably is the key to evaluate the ELSS. At present, some load shedding strategies have certain limitations, which are determined only according to the amount of the load shedding without considering the differences between different loads in an MG. In the actual load shedding process, the differences between different loads can affect the power balance and frequency recovery of the system. This paper comprehensively considers the effects of differences in the load frequency adjustment effect and the load shedding priority. A load shedding contribution indicator is used as the load shedding criterion in the load shedding strategy.

A. THE INDICATOR CONSIDERING THE LOAD FREQUENCY ADJUSTMENT EFFECT

Due to the load frequency adjustment effect, when the power balance of the MG is destroyed and the frequency changes, the following changes in the load power play a role in compensating the system. The frequency adjustment effect coefficient is usually used to quantify the compensation effect of the load in the system, which is expressed as:

$$\begin{cases} K_L = \dfrac{dP_L^*}{df^*} = \displaystyle\sum_{n=1}^{3} n \cdot a_n f^{(n-1)^*} \\ f^* = \dfrac{f}{f_N} \\ P_L^* = \dfrac{P_L}{P_{LN}} \end{cases} \tag{2}$$

where K_L is the frequency adjustment effect coefficient of the load, a_n is the ratio of the load proportional to the nth power of the system frequency to the rated load, P_L is the load power, P_{LN} is the rated power of the load, f is the system frequency, and f_N is the rated frequency of the system.

When the system frequency drops, the loads with large frequency adjustment effect coefficients absorb the less active power from the system, which is beneficial to the frequency recovery. The loads with small frequency adjustment effect coefficients require more power to be absorbed from the system, which is not conducive to the system frequency recovery. Based on the characteristics of the load frequency adjustment, the loads with small frequency adjustment effect coefficients should be preferentially removed during the load shedding process and the loads with large frequency adjustment effect coefficients should be reserved.

B. THE INDICATOR CONSIDERING THE LOAD SHEDDING PRIORITY

The proposed ELSS considers the priority of the load shedding. To ensure the power supply reliability of important loads as much as possible, the secondary loads should be removed first. The loads have been classified as vital, semi-vital, and non-vital. It is represented by L_1, L_2, and L_3 according to the increasing order of the load shedding priority.

C. LOAD SHEDDING CONTRIBUTION INDICATOR

This section considers both the load frequency adjustment effect and the load shedding priority, and establishes the load shedding contribution indicator according to the differential influence mechanism of two indicators, which is as follows:

$$W_i = L_i(\lambda_1 C_1 + \lambda_2 C_2) \tag{3}$$

where W_i is the load shedding contribution indicator, L_i is the priority weight of the load shedding, C_1 is the normalized value of the load frequency adjustment effect indicator, C_2 is the normalized value of the load shedding priority indicator, and λ_1 and λ_2 are the contribution weight coefficients of each contribution indicator.

IV. MG EMERGENCY LOAD SHEDDING STRATEGY BASED ON A DUELING DEEP Q-LEARNING

This section introduces an islanded MG load shedding strategy based on the dueling deep Q-learning in detail. The load shedding strategy is explained from the selections of state sets and action sets, the construction of the Q value function, and the algorithm process of the dueling deep Q-learning.

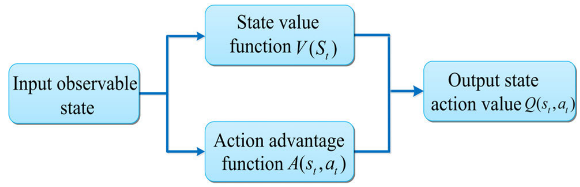

FIGURE 1. Dueling deep Q network.

A. DDQN

The dueling DQN improves the output layer of the evaluation network in the DQN, and the Q value can be expressed in a more detailed form [30]. In the improved DDQN, the Q value function is divided into the action advantage function $A(s_t, a_t)$ and the state value function $V(s_t)$. A neural network is used to fit the state value function $V(s_t)$ under the observation state, and another neural network is used to fit the action advantage function $A(s_t, a_t)$ of each action in the current state. The $Q(s_t, a_t)$ value of each action is obtained by combining the state value function with the action advantage function [31]. The DDQN is shown in Fig. 1. The Q function based on the DDQN structure is defined as follows:

$$Q(s_t, a_t) = V(s_t) + \left[A(s_t, a_t) - \frac{1}{|A|} \sum_{a_t'} A(s_t, a_t') \right] \tag{4}$$

where a_t is the current load shedding action, s_t is the current system state, A represents a set containing all executable load shedding actions, and $|A|$ represents the number of all executable load shedding actions.

Since the actual control can only obtain one Q value, it cannot be disassembled into a unique state value function $V(s_t)$ and action advantage function $A(s_t, a_t)$. Therefore, the action advantage function is set as a single action function minus the average value of all action advantage functions in a certain state to remove redundant degrees of freedom and improve the stability of the algorithm [32]. The flow chart of the algorithm based on the DDQN is shown in Fig. 2.

1) STATE ACTION VALUE FUNCTION

There are a variety of action combinations to choose in the load shedding strategy for an MG. It is necessary to quantify the reward of different actions in the current observation state as the basis for the action selection. According to the observation value of the operating state for an MG, the Q-learning method is used to update the state action estimation function,

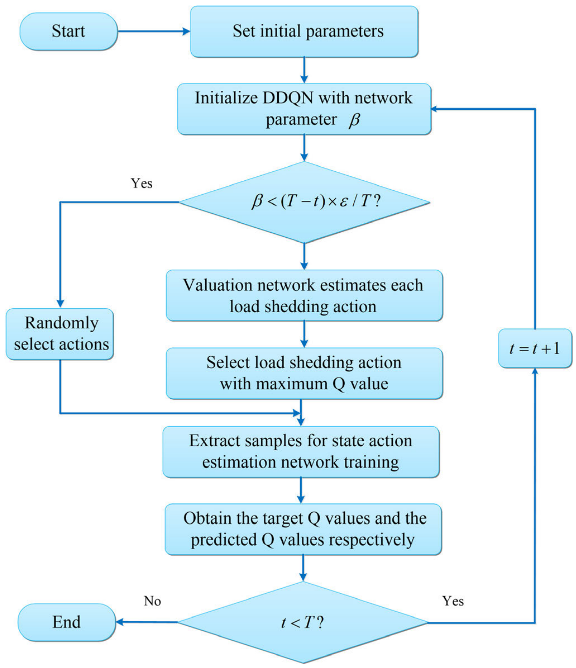

FIGURE 2. **Algorithm flow chart based on DDQN.**

which is as follows:

$$Q^{\pi}(s_t, a_t) \leftarrow (1-\alpha) \times Q(s_t, a_t) + \alpha[r_{t+1} + \gamma \max_{a \in A} Q(s_t, a_t)] \quad (5)$$

where $Q^{\pi}(s_t, a_t)$ is the target value of the optimal state action value function; $Q(s_t, a_t)$ is the predicted value of the current state action value function; α is the learning rate, which satisfies $0 < \alpha \leq 1$; the greater the learning rate, the less the effect of retaining the previous training; based on the Q function iteration, the predicted value can converge to the target value under the condition of sufficient training samples and times; and r_{t+1} is the reward after performing the specific action a_t.

2) $\varepsilon - greedy$ POLICY

A $\varepsilon - greedy$ policy is introduced to select load shedding actions. In the initial stage of offline learning, the load shedding actions can be randomly selected to accumulate observation samples. In the middle and later stages of learning, the observation samples can be effectively used, and the new load shedding actions can be tried. The $\varepsilon - greedy$ policy is used for action selection, which is as follows:

$$a_t = \begin{cases} random\, A, & \beta < (T-t) \times \varepsilon / T \\ \arg\max_{a_t \in A} Q'(s_t, a_t) & \beta \geq (T-t) \times \varepsilon / T \end{cases} \quad (6)$$

where ε is a fixed constant, T is the total number of training times, t is the current training time, and $\beta (0 < \beta \leq \varepsilon)$ is the network parameter of the action advantage function part; if it is less than $(T-t)\varepsilon/T$, the next step of the load shedding action is randomly selected from the executable action set A; otherwise, an optimal action is selected according to the predicted estimate of each action in the current state.

3) NEURAL NETWORK LOSS FUNCTION

During the learning process, the generated samples have uncertainties on the effectiveness of model training and are prone to overfitting. Therefore, the gradient descent method is used for neural network training to prevent overfitting. The neural network loss function is expressed as follows:

$$Loss(\omega) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[Q^{\pi*}(s_t, a_t) - Q^{\pi'}(s_t, a_t, \omega)\right]^2} \quad (7)$$

where $Q^{\pi^*}(s_t, a_t)$ is the target Q value calculated by equation (5), $Q^{\pi'}(s_t, a_t, \omega)$ is the predicted Q value output by the neural network, ω is the neural network structure parameter, and $n$is the number of training samples.

n samples are taken from the memory storage unit each time, and the deviation function is calculated by the mean square deviation between the target value and the predicted value of n samples. The parameters of the neural network are updated by the gradient descent to returns the current maximum Q value; at this time, the optimal strategy is obtained as follows:

$$\pi^*(s) = \arg\max Q^k(s_t, a_t) \quad (8)$$

B. ELSS

In this paper, the ELSS is used to solve the problem of the MG load shedding under the disturbance. The decision flow chart of the MG emergency load shedding based on the dueling deep Q-learning is shown in Fig. 3.

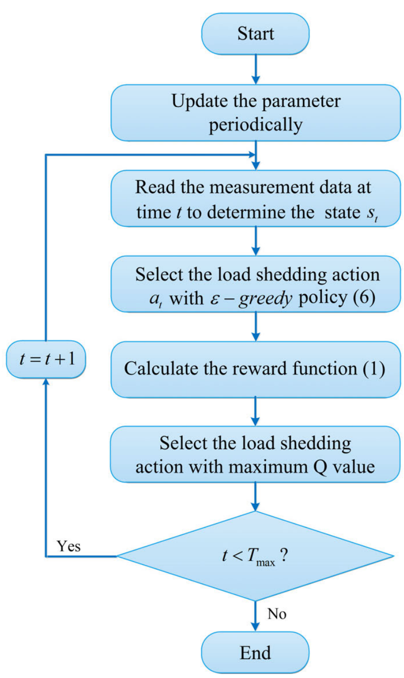

FIGURE 3. **Emergency load shedding decision flow based on dueling deep Q-learning.**

It is a learning process for the dueling deep Q-learning to continuously interact with the environment through an agent and seek the optimal load shedding strategy. In the offline learning process, the agent does not know at first what action the reward and the next state are related to. To maximize the cumulative reward, the agent continuously interacts with the MG operation environment. Specifically, the agent interacts with the MG operating environment in a series of discrete iterative steps, which uses a reward function with the continuous trial-and-error to learn the best behavior. The learning goal is to restore the MG frequency and RoCoF to the normal range and make the environmental state reach the corresponding interval. In each iteration step, the agent observes the environment state and selects a load shedding action. After performing the selected action, the agent receives a reward from the environment. The goal of the agent is to find a suitable strategy to achieve the maximum average reward which is the optimal ELSS.

In online learning, the system makes the fast decision for various scenarios of the MG load shedding based on a large amount of prior knowledge accumulated by offline learning. The load shedding decision-making information stored in the offline knowledge base under different operating environments can quickly guide the online decision-making, which creates conditions for adaptive decision-making under different disturbance scenarios.

V. CASE STUDY

To verify the effectiveness of the ELSS proposed in this paper, a modified IEEE-25 bus islanded MG [33] is built based on the DIgSILENT/POWER FACTORY platform. The MG model is shown in Fig. 4. The MG has 8 DGs and 18 loads. The specific information is shown in Table 1 and Table 2.

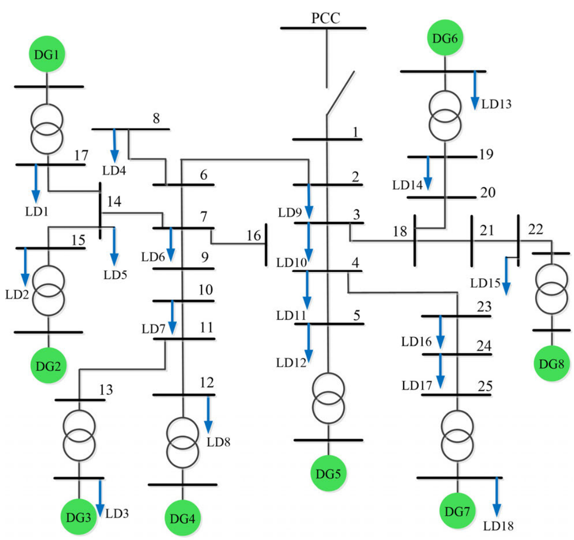

FIGURE 4. MG model based on modified IEEE-25 bus system.

This section compares and analyzes the proposed ELSS and implicit enumeration strategy (IES). Considering the communication transmission delay, the communication transmission delay time is set to 10ms, and the delay of starting the relay and reducing the load is 10ms [34]. The following two cases A and B are set to illustrate the effectiveness of the strategy proposed in this paper.

A. When t = 1s, the distribution network fails and the MG transfers to the islanded operation mode.

B. DGs outage occurs during the load shedding process.

In each case, the islanded operation is simulated by opening the grid circuit breaker at time t = 1s. In the setting of cases, there is a power shortage after the islanded MG operates. These test cases are selected to prove that the ELSS can flexibly adjust the load shedding strategy according to the unexpected disturbance situations and correctly determine the priority of the outage load.

TABLE 1. Load information.

Load category	Load Ranked	Active power load（kW）
Non-vital	LD1	20
	LD2	20
	LD3	10
	LD4	63
	LD5	30
	LD6	35
Semi-vital	LD7	27
	LD8	20
	LD9	20
	LD10	10
	LD11	15
	LD12	25
Vital	LD13	30
	LD14	55
	LD15	50
	LD16	30
	LD17	20
	LD18	30

TABLE 2. Distributed generation information.

DGs	$P_{initial}$(kW)	DGs	$P_{initial}$(kW)
DG1	45	DG5	30
DG2	70	DG6	30
DG3	50	DG7	30
DG4	60	DG8	15

A. CASE 1: MG ISLANDED FROM THE GRID

This case simulates the scenario where the distribution network fails and the MG transfers to the islanded operation mode.

At t = 1s, the MG transfers to the islanded operation mode. Due to the high imbalance between the load power and power generation, the system frequency drops sharply. DGs quickly output active power to supplement the power shortage in the MG, which leads to large fluctuations in the output active power of DGs. Taking DG1 and DG2 as examples, the active power output is shown in Fig. 5(a) and (b).

This section takes S = {0, 0} as the target state, i.e., the system frequency is restored to [49.8, 50.2] Hz, and the RoCoF takes [−1, 0] Hz/s as the safety interval of the load shedding target. After the rapid response of DGs, the system frequency is still lower than 49.8 Hz, which triggers the ELSS.

The load shedding information of the two strategies is shown in Table 3. At this time, the amount of load shedding

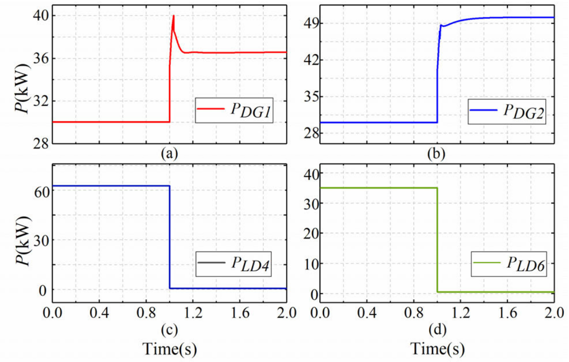

FIGURE 5. Active power output of ELSS in case 1.

TABLE 3. Load shedding strategy comparison results.

Strategies	Load shedding object	Decision-making time (ms)	Minimum frequency (Hz)
IES	Ld 12, 14, 16	35.6	47.75
ELSS	Ld 4, 6	23.9	48.58

calculated by the power shortage equation [15] is 102kW. In the IES, after t = 35.6ms, LDs12, 14, and 16 are decided as the load shedding object. Among them, LDs14 and 16 are vital loads, which result in the power outage of important loads in the system. In the ELSS, according to the current operating state of the MG, load shedding actions are selected to restore the system frequency. Considering the influence of the load shedding contribution indicator, the ELSS remove the non-vital LD4 and LD6 after t = 23.9ms, and the active power of LD4 and LD6 drops to 0 after removing. The power output of LD4 and LD6 is shown in Fig. 5 (c) and (d).

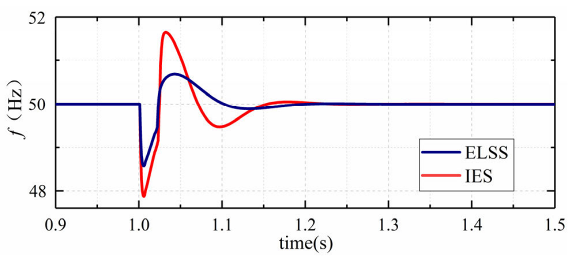

FIGURE 6. Comparison of system frequency transient process in case 1.

To further illustrate the effectiveness of the ELSS in frequency recovery, the comparison of the frequency transient process between the IES and the ELSS is shown in Fig. 6. As can be seen from Fig. 6, the system frequency drops rapidly after the disturbance. The lowest frequency of the ELSS is 48.58 Hz. It is 0.83 Hz less than that of the IES. Compared with the IES, the minimum frequency of the ELSS is reduced by 1.7%. Compared with the rated frequency of 50 Hz, the frequency overshoot based on the IES is 3.4% during the islanding period. The overshoot of frequency based on the ELSS is 1.4%. Compared with the IES, the ELSS reduces the frequency overshoot by 58.82% and greatly reduces the frequency fluctuation amplitude of the MG.

It can be seen from the comparative analysis of load shedding decision-making time and frequency fluctuation that the frequency fluctuation amplitude of the IES is large during the islanding period of the MG, which is not conducive to the safe and stable operation of the MG. At the same time, the load shedding decision time of the ELSS is reduced by 11.7ms compared with the IES, which is conducive to the stable operation of the islanded MG. This is because the principle of the IES is to remove one by one from the end of the line to the direction of the power supply, without considering the different load characteristics. The control performance depends on the accuracy of the physical model to a great extent. In contrast, the strategy proposed in this paper considers the load shedding priority and load frequency regulation effect and is a data-driven load shedding strategy. The ELSS makes fast decisions on different states of the MG based on a large amount of prior knowledge accumulated by the agent offline learning, which greatly shortens the load shedding decision time. At the same time, the frequency adjustment effect guides the decision-making objects to be loads with large frequency adjustment effect coefficients, which improves the frequency recovery effect after load shedding and shortens the frequency recovery time.

The above comparative analyses show that, compared with the IES, the proposed load shedding strategy has superiority in maintaining stable power supply for important loads and reducing the load shedding decision time and fluctuations in the frequency.

B. CASE 2: DG OUTAGE DURING LOAD SHEDDING PROCESS

Based on the MG islanded operation, Case 2 simulates the scenario where DGs quit operation due to a fault and the power shortage of the MG increases.

Case 2 simulates the scenario where DGs quit operation while the MG transfers to the islanded operation mode. At t = 1s, the MG transfers to the islanded operation, and DG3 and DG4 quit the operation due to the abnormal disturbance. The system power shortage is further amplified. At this time, the DGs respond quickly to make up for the power shortage. The active power output of DGs1, 2, 3, and 4 under this case is shown in Fig. 7.

The load shedding information of the two strategies is shown in Table 4. Under this condition, the amount of load shedding calculated by the power shortage equation [15] is 143 kW. In the IES, the load shedding objects determined at t = 1.0362s are LDs1, 5, 8, 14, and 17. This strategy does not guarantee the stable power supply for the vital load LDs13, 14, and 15. At t = 1.0242s, the removed object decided by the strategy proposed in this paper is non-vital load LDs1, 2, 4, and 6, which does not cause the important load outage. At the same time, the decision time of the ELSS is reduced by 12ms compared with the IES, which shortens the load shedding decision time and avoids the greater damage to the system. The comparison of the above load shedding decision time shows that the ELSS decision-making time is short and the non-vital load is removed quickly, which is conducive to the frequency stability of the system. The rotational inertia of DGs in the MG is usually very small and the frequency stability is poor. The frequency change rate is very fast in case of power shortage, so it is necessary to reduce the load quickly.

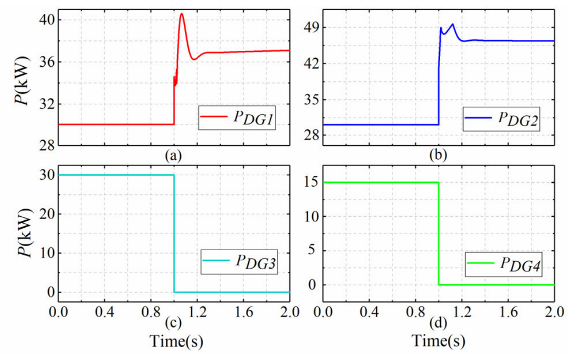

FIGURE 7. Active power output of ELSS in case 2.

TABLE 4. Load shedding strategy comparison results.

Strategies	Load shedding object	Decision-making time (ms)	Minimum frequency (Hz)
IES	Ld 1, 5, 8, 14, 17	36.2	47.1
ELSS	Ld 1, 2, 4, 6	24.2	48.53

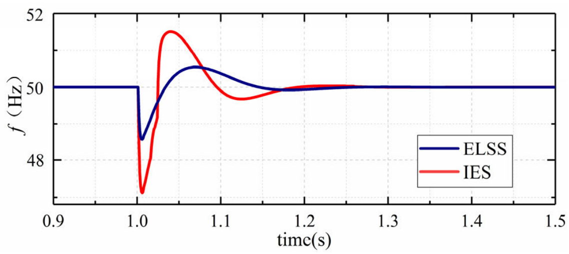

FIGURE 8. Comparison of system frequency transient process in case 2.

The comparison of the frequency transient process between the IES and the ELSS is shown in Fig. 8. It can be seen from Fig. 8 that the system frequency drops rapidly after the disturbance occurs. The lowest frequency of the IES is 47.1 Hz. The lowest frequency of the ELSS is 48.53 Hz, which is 1.43 Hz less than the lowest frequency of the IES. Compared with the rated frequency, the overshoot of the frequency based on the IES is 2.88%, and it is stable after 0.3s. Based on the proposed strategy, the overshoot is 1.12%. After 0.189 s, it is stable. Compared with IES, the proposed strategy reduces frequency overshoot by 61.11% and frequency recovery time by 37%.

In terms of the system frequency recovery, the frequency adjustment effect guides the decision-making objects to be loads with large frequency adjustment effect coefficients, so that the frequency recovery time is shortened. The ELSS recovers to a stable state after t = 189ms, while the IES needs to stabilize after t = 300ms, which is 111ms more than the proposed strategy.

To sum up, the ELSS can achieve the stable operation of the system under different disturbances. It not only has advantages in the system frequency fluctuation and system stability recovery but also takes into account the cost of the load shedding more reasonably.

VI. CONCLUSION

This paper defines the problem of the MG emergency load shedding as an MDP problem. In the load shedding strategy, the importance of loads and the frequency recovery time of the system are considered first. To solve this load shedding problem, this paper uses the load shedding contribution indicator as a criterion of the load shedding strategy. On this basis, a method based on the dueling deep Q-learning is proposed to determine the optimal load shedding strategy. In this strategy, the action advantage function and state value function are used to accelerate the convergence and improve the stability of the algorithm. The ELSS is used to learn offline and generate the optimal load shedding decision, which shortens the online decision-making time. The simulation results show that the performance of the proposed strategy is better than that of the model-driven load shedding strategy in maintaining stable power supply for important loads and reducing the load shedding decision time and frequency fluctuations. In addition, this strategy can adjust the load shedding strategy according to the specific operation of the MG to solve the load shedding problem under different disturbance scenarios.

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