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THREE-STATE ENERGY VOLTAGE REGULATION MODEL APPLIED TO SMART GRID

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Abstract

Based on various intelligent technologies, smart grids can effectively ensure voltage stability, achieve large-scale and cross regional power dispatching, and make power resource allocation more reasonable. However, with the continuous integration of various emerging energy sources, the voltage regulation in smart grids faces more complex and ever-changing external environments. The stability control of voltage regulation is challenged. To enhance voltage regulation in smart grids, this study proposes a model based on the three-state energy (TSE) structure. A Markov game (MG) model is introduced to perform regional calculations on the smart grid. A distributed calculation method for voltage regulation in the smart grid is constructed. The experimental results showed that the IAE, ISE, ITAE, ITMSE, ISTAE, and ISTSE of the voltage regulation method were 0.0051, 0.0056, 0.027, 0.0024, 5.57, and 0.00468, respectively. All error integration criteria are lower than other commonly used voltage regulation methods. The research results have important reference significance for effectively implementing voltage control in smart grids, optimising voltage control methods, and improving the stability and reliability of power supply.

Key Words

Smart grid, three-state energy, voltage regulation, Markov model

1. Introduction

The smart grid is based on advanced sensors and controllers. Power system monitoring and data analysis help to accurately regulate voltage, maintain system voltage stability, ensure power supply, and coordinate distribution [1]–[3]. With the continuous promotion of various clean energy sources, distributed renewable energy is widely used in distribution networks, which also exacerbates the voltage instability problem in intelligent distribution networks. The compensation state of smart grid includes three types of reactive power compensation states, reactive power generation, reactive power absorption, and shutdown state, which are the three-state energy (TSE) structure [4]. Traditional voltage regulation techniques include transformer voltage regulation, capacitive compensation, and reactive power control, which can ensure voltage stability [5], [6]. However, faced complex smart grid systems, these regulation effects are limited, and may even lead to unpredictable behaviour of voltage regulation equipment. Therefore, the study aims to address the intermittency of distributed energy sources and the dynamic changes in voltage in smart grids, dynamically control the smart grid voltage, and improve voltage control accuracy. Based on the TSE structure, a Markov game (MG) model is introduced to regulate and control the voltage in the smart grid. Meanwhile, the study introduces Attention Mechanism (AM) to optimise. A MG-AM model is constructed to optimise the operational stability of the smart grid, improve power quality, and reduce energy consumption. The innovation of the research is as follows. MG provides the optimal decision-making framework in dynamic environments, while AM optimises the decision-making process by focusing on key information. The combination of the two enables the control system to generate optimal control strategies more efficiently in complex environments, significantly improving the system's dynamic response capability, optimising the control strategy, and enhancing robustness.

The contributions of this study are as follows. First, this study constructs a voltage regulation model based on MG and introduced AM to optimise the regulation process. Based on the designed MG-AM voltage regulation control model, the operation of smart grid has been further optimised, the stability of voltage has been enhanced, the power quality has been further improved, and energy consumption has been reduced.

The main challenge that this study attempts to address is the uncertainty of the power grid and the efficiency of multi-agent collaborative control. In the smart grid, the intermittency of distributed energy, load fluctuations, and equipment failures can all lead to frequent voltage changes. Therefore, an MG model is introduced to partition the

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smart grid for calculation, thereby achieving distributed voltage calculation in the smart grid and effectively optimising voltage stability.

The study consists of four parts. The first part summarises the research status of voltage regulation and MG both domestically and internationally. The second part first conducts zoning calculations on the smart grid and then designs a voltage regulation method based on MG theory. The third part conducts experimental analysis on the proposed method. The fourth part summarises the research content and proposes future research directions.

2. Related Works

Voltage regulation is one of the important means to ensure the stable, safe, and economical operation of the power system. Scholars have conducted in-depth research on voltage regulation methods. Liu *et al.* developed a fully decentralised dual loop energy trading mechanism with voltage regulation capability. Energy production consumers iteratively achieved optimal energy transactions through multi-bilateral negotiations without considering network constraints. The effectiveness and efficiency of the proposed solution were verified through multiple cases [7]. Giacomuzzi *et al.* introduced a medium voltage power grid based on intelligent transformers, which supported the medium voltage power grid through active power control in the low-voltage power grid powered by intelligent transformers. Compared with similar solutions, the research method improved reactive power compensation [8]. Yadav *et al.* discussed the system reliability performance of the restructured power system. Peak load capacity (PLCC) could be observed when the generator set was unavailable and new generator sets were added to the system. The impact of generator maintenance was also observed in terms of risk level and reliability performance [9].Mahajan *et al.* proposed a transmission line model to simulate the propagation characteristics of transmission line switches as the load changes. The synchronous phasor measurement device exhibited anomalies due to information intrusion or equipment failure in the communication network, making the system observable and characterising the fragile behaviour of transmission lines [10]. Paniagua *et al.* proposed a new integrated circuit control strategy called Dual Inertia Simulation. This strategy improved the dynamic response of the connected power grid by simulating the inertia on both sides of the converter. The results indicated that it increased the equivalent inertia response [11].

MG is a statistical model extensively applied in natural language processing fields such as phonetic conversion, probabilistic grammar, part of speech automatic labeling, *etc.* Frimane *et al.* [12] introduced an infinite hidden MG for short-term probability prediction of solar irradiance. It could automatically adapt to the complexity of "correction." The results showed that the prediction range had higher consistency. Abraham *et al.* investigated the boundary between learnable and non-learnable hidden Markov model (HMM). The known model parameters were fully recognisable without making any modelling assumptions about the distribution of the population. As long as the clusters were different, the hidden chain was a traversal chain with a full rank transition matrix[13]. Flandoli *et al.* proposed a virus diffusion model based on Markov chain individuals. This model effectively captured the statistical variability in Tuscany [14]. The comparison of relevant studies is shown in Table 1.

In summary, voltage regulation in smart grids can effectively achieve stable operation of power equipment, but there are also shortcomings in these studies. Specifically, the voltage regulation method proposed by Liu *et al.* can achieve better energy trading, but it does not take into account specific constraints such as network constraints. The medium voltage power grid distribution method proposed by Giacomozzi *et al.* lacks sufficient consideration for large-scale energy deployment environments. The integrated circuit control strategy proposed by Paniagua *et al.* has not been further validated for its scalability. Overall, there are shortcomings in the voltage regulation of smart grids at present. Most studies adopt centralised voltage control methods, which are difficult to be well applied in large-scale distributed energy smart grids. Therefore, the MG model is taken for voltage optimisation control in smart grids. It is expected to further optimise the voltage regulation and achieve stable operation of power equipment.

3. Construction of a TSE Voltage Regulation Model-based on MG-AM

To better achieve voltage regulation control in smart grids, an MG is adopted to optimise voltage regulation control in smart grids based on existing voltage regulation models. A parallel voltage control method for smart grids is constructed by performing regional calculations.

3.1 Construction of Voltage Regulation Problem Based on TSE Structure

With the continuous integration of distributed energy into smart grids, the difficulty of voltage stability control is gradually increasing. The compensation states of flexible loads and traditional reactive power compensation connected to the smart grid include reactive power generation, reactive power absorption, and shutdown states. If the above three reactive power compensation states are met, it is a TSE structure. This structure can regulate flexible loads, reduce the operating time of reactive power compensation equipment in smart grid voltage control engineering, and thus extend the service life of the equipment [15]. These three types of compensation states all have impacts on the voltage. The basic structure is shown in Fig. 1.

In Fig. 1, when the TSE unit is in a reactive state, the energy structure provides reactive power to the smart grid. When it is in a state of absorbing reactive power, it simultaneously absorbs the reactive power of the smart grid. When the energy structure is in a shutdown state, there is no interaction between the TSE structure and the smart grid. At this time, the

Table 1
The Comparison of Relevant Studies

Reference	Method/Content	Advantages	Disadvantages
Liu *et al.* [7]	A fully decentralised dual loop energy trading mechanism	Achieved optimal energy transactions	It does not take into account specific constraints such as network constraints.
Giacomuzzi *et a.l* [8]	A medium voltage power grid based on intelligent transformers	Improved reactive power compensation	Lack sufficient consideration for large-scale energy deployment environments.
Yadav *et al.* [9]	Discussed the system reliability performance of the restructured power system.	Risk level and reliability can be observed	/
Mahajan *et al.* [10]	A transmission line model to simulate the propagation characteristics	Make the system observable and characterise the fragile behaviour of transmission lines	/
Paniagua *et al.* [11]	A new integrated circuit control strategy called Dual Inertia Simulation	Improved the dynamic response	The scalability has not been further validated
Frimane *et al.*[12]	Introduced an infinite hidden MG for short-term probability prediction	High consistency	Higher computational complexity
Abraham *et al.*[13]	Investigated the boundary between learnable and non learnable HMM	Model parameters were fully recognisable	High computational load
Flandoli *et al.* [14]	A virus diffusion model based on Markov chain individuals	Effectively captured the statistical variability in Tuscany	The applicability in different scenarios has not been verified

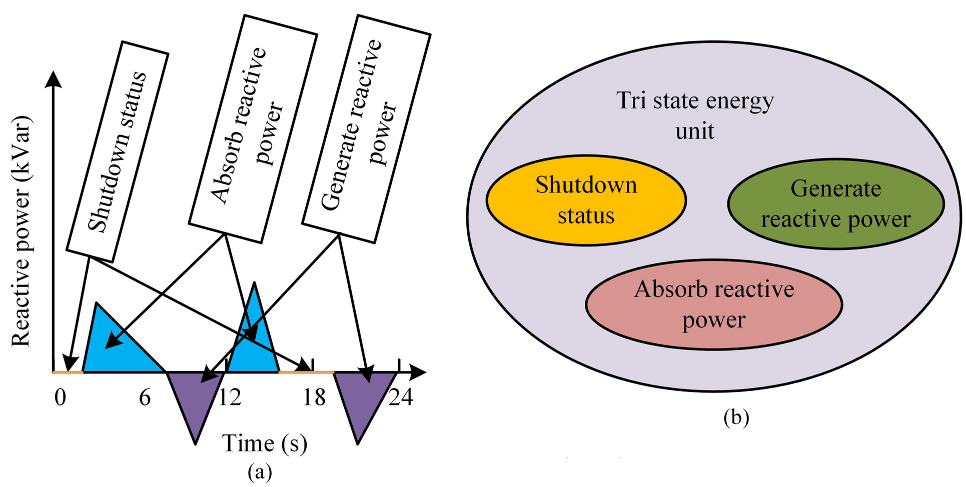

Figure 1. Schematic diagram of voltage regulation for TSE sources; (a) Power regulation and (b) Three state energy structure.

voltage of the smart grid remains unchanged [16]. In an intelligent distribution network, an environment containing D photovoltaic inverters is represented as $N(m,r)$, r represents the node set of the photovoltaic inverter and m represents the set of all nodes. At time t, the safe voltage range of node h is shown in (1)

$$V_{\min} \leq V_{h,t} \leq V_{\max}, h \in m \tag{1}$$

In (1), V represents the voltage. $V_{\min}$ and $V_{\max}$ represent the safe upper and lower limits of the voltage. While ensuring voltage safety, the active and reactive power constraints of all photovoltaic inverters are shown in (2)

$$(P^{a}_{i,t})^2 + (P^{\mathrm{ua}}_{i,t})^2 \leq S_i^2, i \in r. \tag{2}$$

In (2), $P^{a}_{i,t}$ represents the active power that has not been adjusted, $P^{\mathrm{ua}}_{i,t}$ represents the unadjusted reactive power and S_i^2 represents the actual power. The power flow balance of each node i is shown in (3)

$$\begin{cases} P_{i,t}^{a} - P_{i,t}^{\text{load}} = V_{i,t} \sum_{h=1}^{m} V_{h,t}(G_{i,h,t} \cos\theta_{i,h,t} \\ \qquad\qquad +B_{i,h,t} \sin\theta_{i,h,t}) \\ P_{i,t}^{\text{ua}} - P'^{\text{load}}_{i,t} = V_{i,t} \sum_{h=1}^{m} V_{h,t}(G_{i,h,t} \sin\theta_{i,h,t} \\ \qquad\qquad +B_{i,h,t} \cos\theta_{i,h,t}) \end{cases} . \tag{3}$$

In (3), $P_{i,t}^{\text{load}}$ and $P'^{\text{load}}_{i,t}$ represent the uncontrollable active and reactive power of node i at time t. $B_{i,h,t}$ and $G_{i,h,t}$ are real and imaginary numbers between node i and node h. In uncertain environments, the voltage regulation problem of smart grids is shown in (4)

$$\text{Ques1} = \Theta \left\{ \sum_{t=1}^{T} \sum_{i=1}^{N} |\Delta_{\text{Deviation}}| \right\} \tag{4}$$

In (4), Θ represents the expected factor for system parameters such as photovoltaic power generation, load demand, and possible stochastic decisions, $\Delta_{\text{Deviation}}$ represents the voltage deviation and Ques1 represents an optimisation problem. Based on the above process, a mathematical model for voltage regulation in smart grids is obtained.

3.2 Construction of Voltage Regulation Model–based on MG

Based on the established mathematical model of voltage regulation, the voltage is regulated. The traditional voltage control methods often adopt centralised voltage control methods, which are difficult to be well applied in large-scale energy distributed smart grids. Therefore, an MG model is introduced to solve the target problem. In MG, each agent can take different actions at every moment, which can affect the benefits and state transitions of other agents [17]. The photovoltaic inverter is simulated as an intelligent agent. The distribution network is an environment for exchanging with intelligent agents. The voltage control problem of photovoltaic inverters is simulated as a MG with N agents, as shown in Fig. 2.

First, partition calculation is performed on the intelligent distribution network. The Jacobian matrix is obtained using power flow calculation, as shown in (5)

$$\begin{bmatrix} \Delta \text{P} \\ \Delta \text{Q} \end{bmatrix} = \begin{bmatrix} A_{\text{P}\delta} & B_{\text{PU}} \\ C_{\text{Q}\delta} & D_{\text{QU}} \end{bmatrix} \begin{bmatrix} \Delta\delta \\ \Delta \text{U} \end{bmatrix} \tag{5}$$

In (5), ΔP and ΔQ refer to the changes in active and reactive power connected by the node. ΔU and $\Delta\delta$ represent the changes in voltage amplitude and phase angle at the node, respectively. $A_{\text{P}\delta}$ and B_{PU} both represent the relationship between the changes in active and reactive power connected to the node and the voltage amplitude of the node. $C_{\text{Q}\delta}$ and D_{QU} represent the relationship between the changes in active and reactive power connected at the node and the changes in phase angle. After matrix

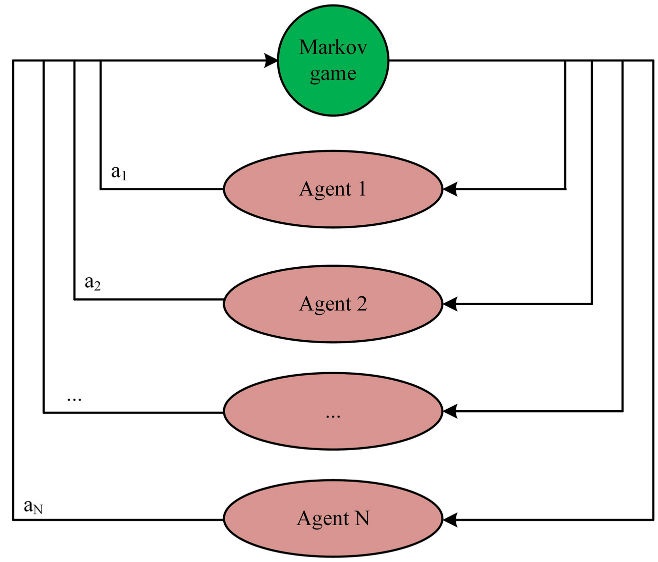

Figure 2. Basic schematic diagram of MG model.

transformation, it is shown in (6)

$$\begin{bmatrix} \Delta\delta \\ \Delta \text{U} \end{bmatrix} = \begin{bmatrix} S_{\text{P}\delta} & S_{\text{Q}\delta} \\ S_{\text{PU}} & S_{\text{QU}} \end{bmatrix} \begin{bmatrix} \Delta \text{P} \\ \Delta \text{Q} \end{bmatrix} . \tag{6}$$

In (6), $S_{\text{P}\delta}$ represents the impact of unit quantity of active power input on the phase angle of node voltage, $S_{\text{Q}\delta}$ represents the impact of reactive power input on the phase angle of node voltage. S_{PU} and S_{QU} represent the impact of active and reactive power on the voltage amplitude at the node. Voltage regulation is completed by adjusting the reactive power of photovoltaic inverters and reactive power compensators. The study adopts spectral clustering method to achieve distribution network partitioning calculation. The fully connected method is used to construct the adjacency matrix Z. The element in row x and column y is shown in (7)

$$Z_{x,y} = \sum_{x=1,y=1}^{N} exp(\frac{-\left\| f_x - f_y \right\|^2}{2\sigma^2}) \tag{7}$$

In (7), f_x represents the x-th element of the matrix and σ is the coefficient that controls the adjacency matrix. Then, it is transformed into a clustering problem, with the objective function shown in (8)

$$G(T_1, T_2, ..., T_k) = \frac{1}{2} \sum_{x=1}^{k} \sum_{a \in T_k, b \in \overline{T}_k} \text{vol}(T_k) \tag{8}$$

In (8), k represents the number of clusters, T_r represents the r-th cluster in the clustering results, $\overline{T}_r$ represents the complement of T_r and vol(T_r) represents the weighted sum of all edges. The distribution network is divided into multiple sub networks, as shown in Fig. 3.

Based on the partition results, the voltage optimisation regulation is transformed into multiple sub problems solved in parallel. The voltage collaborative control problem is constructed as an MG, where each sub network is

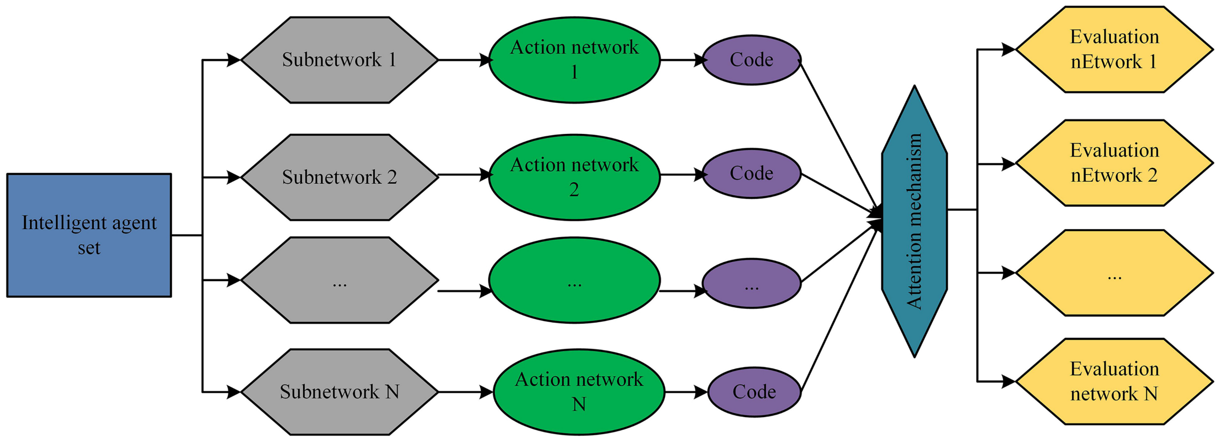

Figure 3. Intelligent distribution network division.

an agent. At different time points, each agent makes scheduling decisions based on the corresponding sub network information [18]. At time t, N_t^j is the local observation information of the sub network of agent j in the agent set N. All agent actions are included in action set A. The action a_t^j of agent j is a controllable device scheduling instruction for the sub network. $r_t^j \in R_t$ represents the immediate reward received by agent j after executing the action, as displayed in (9) [19]

$$r_t^j = -\sum_{i \in N} |V_{i,t} - V_0| + \beta. \tag{9}$$

In (9), $\sum_{i \in N} |V_{i,t} - V_0|$ represents the voltage offset of all nodes and β represents the penalty term when the node voltage exceeds the limit. At time t, the agent j makes a scheduling decision a_t^j based on the local information N_t^j of the sub network. After all agents have executed the scheduling decision, they receive a reward value r_t. Then, the system enters the next state. In MG, each agent maximises the cumulative discount reward by giving a scheduling instruction a_t^j. To solve the MG model, each sub network obtained is defined as a double delay deep deterministic agent. Each intelligent agent is composed of an action function and an evaluation function. The input of the action function is the local observation information N_t^j of the corresponding sub network of the intelligent agent. The output data is the scheduling instruction a_t^j for controllable devices within the sub network, as shown in (10)

$$a_t^j = p_j(s_t^j). \tag{10}$$

In (10), $p_j(\cdot)$ represents the action function of the fitted agent j. The input of the evaluation function is the global information (S_t, A_t). The output of the evaluation function is a scalar indicating the action value of the agent in the current state. The action function and evaluation function complement each other, as shown in (11) [20]

$$Q_j(S_t, A_t) = g_j(S_t, A_t). \tag{11}$$

In (11), $g_j(\cdot)$ represents the evaluation function of the fitted intelligent agent j, $Q_j(\cdot)$ represents the evaluation function and A_t represents the action of all intelligent agents. In the provided equations, first, the voltage changes in the smart grid are represented by mathematical symbols, thus using mathematical equations to represent the entire change process. Then, the agent relationships in the MG model are represented and calculated using mathematical symbols. Therefore, the calculation process can be completed.

MG divides the power grid into multiple control zones, each of which is treated as an intelligent agent. Intelligent agents make independent decisions based on local observation results, such as node voltage, while coordinating global goals through game mechanisms, such as reducing network losses and stabilising voltage. MG obtains voltage uncertainty changes through the state transition probability matrix to adapt to real-time voltage changes and complete voltage prediction.

3.3 Construction of Voltage Regulation Model–based on Improved MG

To ensure the control effect of multiple agents in a certain scene, AM is introduced to optimise its control to ensure that the agents concentrate their "attention" on information related to their own reward values during training, ensuring the control effect [21]. In an MG with N agents, the parameter set to be optimised is represented as $\theta = \{\theta_1, \theta_2, ..., \theta_N\}$. For the agent j, the parameter to be optimised is represented as $\theta_j = \left\{\theta^{\mu_j}, \theta^{\mu_j'}, \theta^{Q_j}, \theta^{Q_j'}\right\}$. θ^{μ_j} and $\theta^{\mu_j'}$ represents the action network and target action network of agent j, respectively. θ^{Q_j} and $\theta^{Q_j'}$ represents the parameters of the attention network and the target attention network, respectively. The implementation process of voltage regulation control using MG improved by AM is shown in Fig. 4.

Based on the above calculation, a TSE voltage regulation model is established to perform distributed voltage control on the smart grid. The entire smart grid system is divided into W sub regions, each with a central bus reflecting the voltage of that region. Then, the optimisation control is achieved through regional autonomous control and coordinated control between

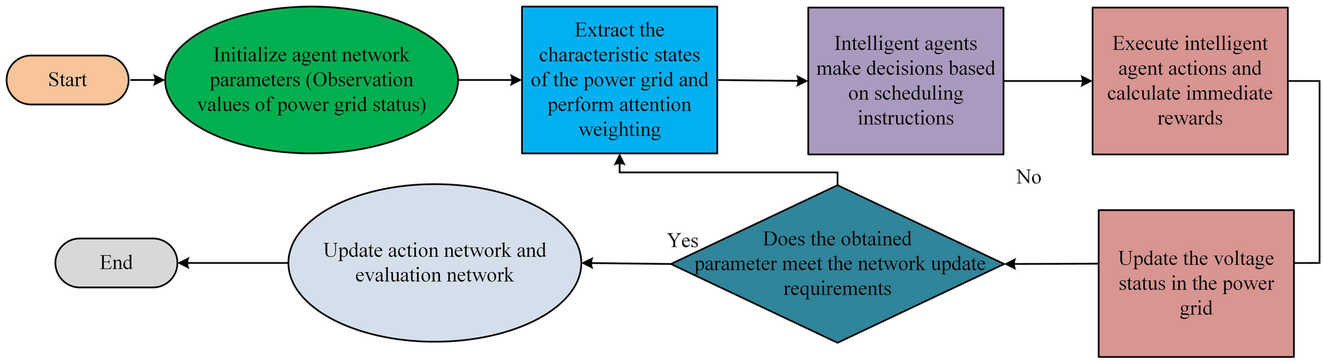

Figure 4. Implementation process of voltage regulation control based on MG optimised by AM.

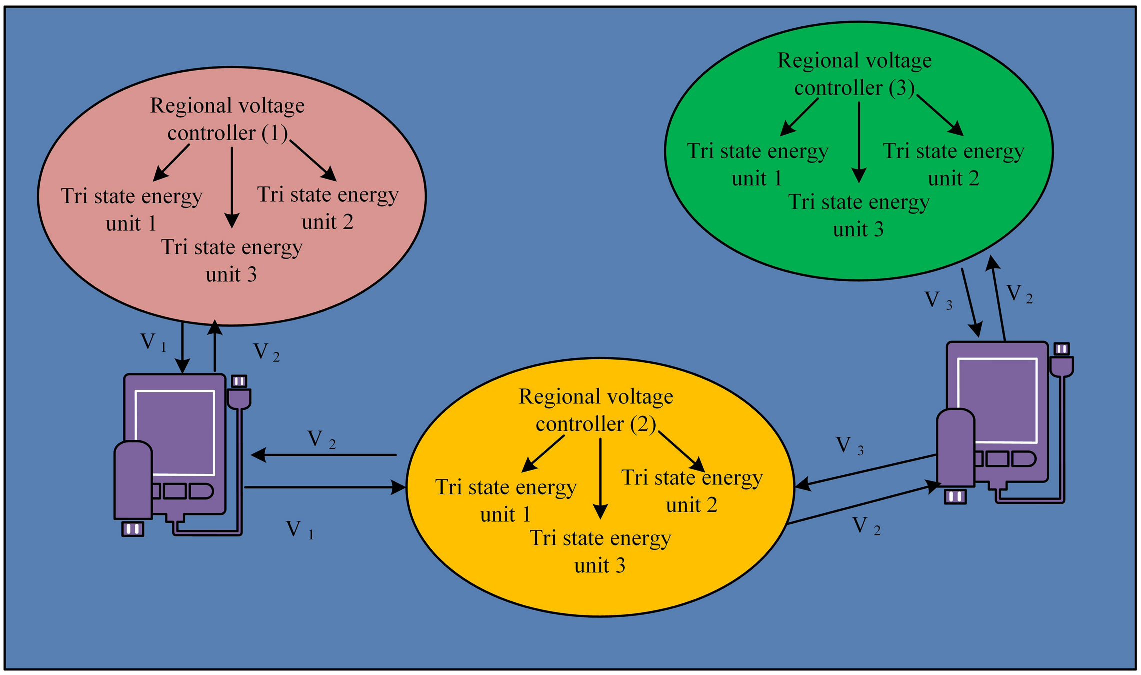

Figure 5. Distributed voltage control for smart grid.

different regions. The basic framework is displayed in Fig. 5.

In this voltage control framework, the voltage control of each region can be regarded as an intelligent agent. All intelligent agents learn the optimal action strategy within this control region. After completing training, the intelligent agents execute the optimal action based on the obtained information. If an intelligent agent in a certain area is unable to effectively handle reactive power redundancy, adjacent intelligent agents can achieve reactive power absorption or provision for that area through regional connections.

4. Performance Analysis of TSE Voltage Regulation Model–based on MG

To verify the actual effectiveness of the proposed method, corresponding experiments are designed to analyse. Then, the method is specifically applied to the voltage state analysis of a day in a certain place to verify the actual application effect.

4.1 Performance Analysis of Voltage Regulation Model

To verify the performance, experimental analysis is conducted by collecting actual 300 days of photovoltaic power generation data from a certain location in a year. The training set consists of 280 days and the test set has 20 days. The maximum deviation of node voltage is $\pm 5\%$. A total of 50 units are arranged. The performance analysis is conducted in an IEEE33 node system. The experimental environment is as follows. The processing system is Windows 10, the processor is Intel Core i5-10210U, the main frequency is 1.60 GHz, and the memory is 16 GB. The simulation experiment is completed in MATLAB2020b. First, the average voltage offset under different partition numbers is analysed in the test set. The designed method is compared with stochastic programming and centralised control methods. Table 2 displays the results. The maximum, minimum, and average voltage offsets of the MG-AM method were all relatively low. Under different numbers of partitions, the voltage offset of the

Table 2
Voltage Offset Under Different Partition Quantities

Number of partitions	MG-AM			Stochastic programming			Centralised control		
	Maximum	Minimum	Average	Maximum	Minimum	Average	Maximum	Minimum	Average
2	2.28%	0.03%	0.15%	5.34%	1.02%	0.19%	2.66%	0.34%	0.16%
3	1.75%	0.01%	0.14%	4.37%	0.95%	0.19%	3.12%	0.56%	0.17%
4	2.03%	0.01%	0.15%	4.98%	0.98%	0.20%	2.98%	0.28%	0.16%
5	1.15%	0.02%	0.13%	3.85%	0.56%	0.22%	4.06%	0.95%	0.20%
6	1.49%	0.01%	0.13%	3.67%	0.94%	0.20%	3.57%	0.41%	0.16%

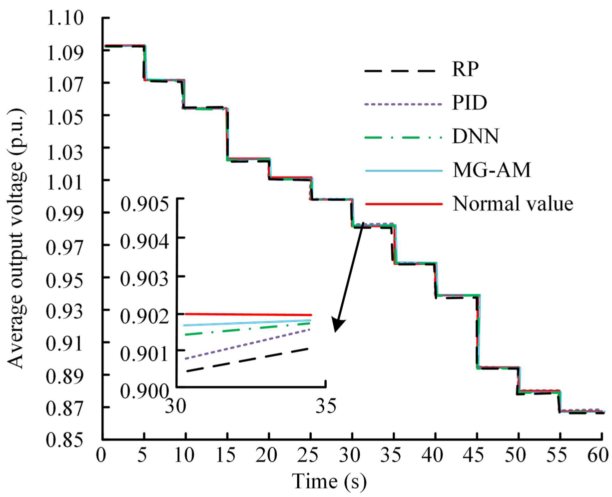

Figure 6. AOV under different control strategies.

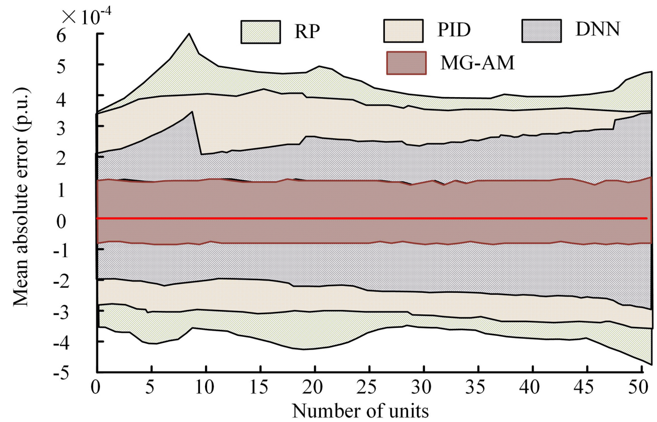

Figure 7. Average absolute error of output voltage.

method used in the study was lower than that of stochastic programming and centralised control methods. As the number of partitions increased, the maximum, minimum, and average values of the MG-AM model overall showed a downward trend. The maximum and minimum values of the stochastic programming method showed a downward trend, while the mean slightly increased. The voltage offset of centralised control fluctuated up and down. Overall, the study selected 5 partition numbers for the study.

The designed method is compared with the commonly used methods, including proportional-integral-derivative (PID) voltage control method, deep neural network (DNN) voltage control method, and random programming method (RP). First, the average output voltage (AOV) is used to measure the voltage output status of each unit, which represents the AOV of the TSE unit. The AOV of the four methods during a certain period of time is shown in Fig. 6. The differences among several methods were significant within 30–35 s. The RP method had the largest deviation from the normal value, which was 0.0016. The PID had a deviation from the normal value of 0.0013, the DNN was 0.0005, and the MG-AM was 0.0003. Therefore, the AOV value of the MG-AM is the reference value, with relatively better performance.

The mean absolute error (MAE) of the three methods is shown in Fig. 7. The MAE value had significant differences in different units. Specifically, the MAE of the RP appeared in $-4.8 \times 10^{-4} - 5.9 \times 10^{-4}$. The PID was within $-3.1 \times 10^{-4} - 4.4 \times 10^{-4}$, and the DNN was in the $-3.3 \times 10^{-4} - 3.5 \times 10^{-4}$. The MG-AM method was within the range of $-0.8 \times 10^{-4} - 1.2 \times 10^{-4}$. The error value of all units is the smallest, indicating that the voltage control effect obtained by designed method is better.

The error integration criterion is commonly used to analyse control performance, which includes six sub criteria, namely the integral absolute error (IAE), the integral squared error (ISE), integral time multiple absolute error (ITAE), Integral Time Multiple Square Error (ITMSE), Integral Squared Time Absolute Error (ISTAE), and Integral Squared Time Squared Error (ISTSE). The above criteria are used to analyse the research method. The error integral criterion analysis results obtained are shown in Fig. 8. In Fig. 8(a), the IAE values for RP, PID, and DNN were 0.0076, 0.0064, and 0.0054, and MG-AM was 0.0051. In Fig. 8(b), the ISE values for RP, PID, and DNN, and MG-AM were 0.0069, 0.0068, 0.0062, and 0.0056, respectively. In Fig. 8(c), the ITAE values for RP, PID, DNN and MG-AM were 0.046, 0.038, 0.029, and 0.027, respectively. In Fig. 8(d), the IAE values for RP, PID, DNN, and MG-AM were 0.00244, 0.00223, 0.00211, and 0.00204, respectively. In Fig. 8(e), the IAE values for RP, PID, and DNN, and MG-AM were 8.21, 7.99, 5.92, and 5.13, respectively. In Fig. 8(f), the IAE values for RP, PID, DNN, and MG-AM were 0.00489,

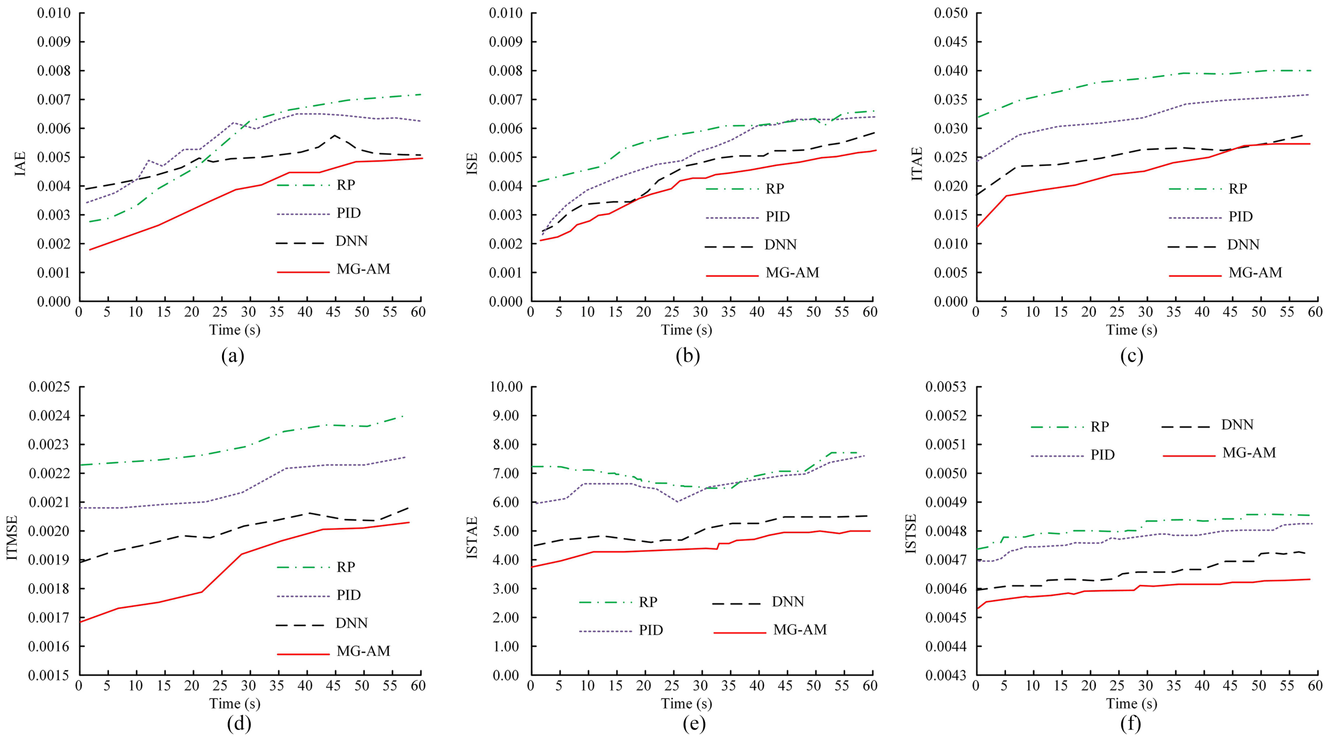

Figure 8. Comparison of error integration criteria: (a) IAE; (b) ISE; (c) ITAE; (d) ITMSE; (e) ISTAE; and (f) ISTSE.

0.00485, 0.00476, and 0.00463, respectively. The error integral criterion results of the designed control method are lower than those of other commonly used voltage regulation methods.

4.2 Application Effect Analysis of MG-AM Model

To further analyse the reliability, a day with sufficient lighting in a certain southern area is selected for analysis. Meanwhile, the node system is transformed to further verify the potential impact of the node system on the control method. The voltage distribution on the same day under different control strategies is shown in Fig. 9. The voltage distribution controlled by the RP fluctuated the most throughout the day, followed by the PID. The voltage distribution under the DNN and MG-AM methods was relatively stable and concentrated. However, the voltage controlled by the DNN was relatively low, with a significant deviation from the normal value of 1.00 p.u. Therefore, the voltage distribution controlled by MG-AM is relatively stable and concentrated, and tends towards the reference value of 1.00 p.u. Therefore, its performance is superior to other methods.

The output voltage effects obtained under different control methods are shown in Fig. 10. In Fig. 10(a), in the IEEE33 node system, the proposed MG-AM method had the smallest output voltage fluctuation, with a range of [0.98–1.02]. The output voltage fluctuation ranges of RP, PID, and DNN were [1.00–1.08], [0.88–1.06], and [0.94–1.02], respectively. PID had the largest fluctuation range and the output voltage was the most unstable. In Fig. 10(b), the output voltage fluctuation ranges of RP,

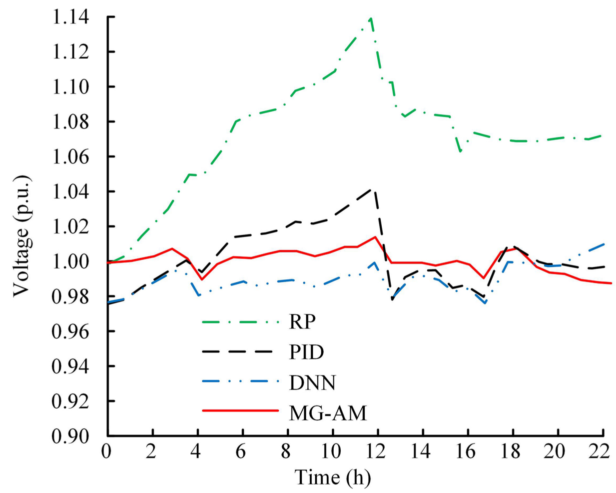

Figure 9. Voltage distribution under different control strategies.

PID, and DNN were [1.00–1.12], [0.94–1.02], and [0.97–1.02], respectively. The output voltage fluctuation range of MG-AM was [0.99–1.03]. The fluctuation trend of RP was the most significant. Overall, the proposed method has the most stable output voltage, which can effectively achieve voltage stability regulation in smart grids, ensuring effective voltage output.

The energy utilisation efficiency in the power grid is analysed. Figure 11 displays the results. After the end of the day, there was a significant difference in the cumulative energy utilisation efficiency under different methods. Specifically, the cumulative energy utilisation efficiency based on RP method was 0.38, while the

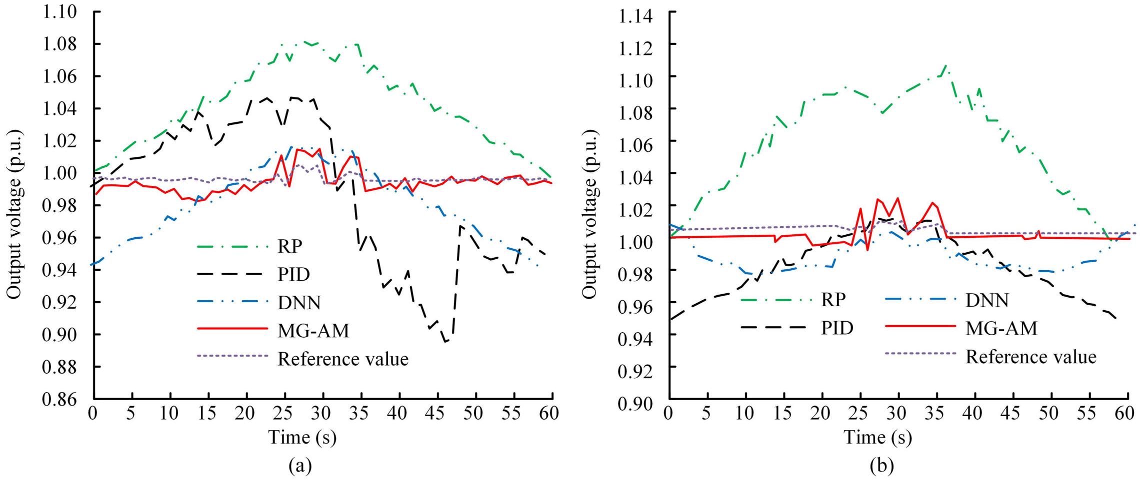

Figure 10. Voltage distribution at the same node: (a) IEEE 33 and (b) IEEE 123.

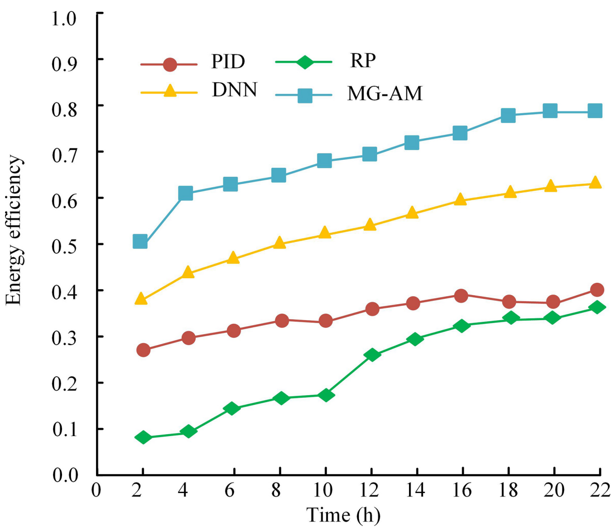

Figure 11. Energy saving efficiency under different power grid dispatch scenarios.

cumulative energy utilisation efficiency based on PID and DNN voltage regulation was 0.43 and 0.66. The cumulative energy utilisation efficiency of the research method was 0.83. The designed voltage regulation method can effectively improve energy utilisation efficiency and reduce energy waste in smart grids.

To validate the research results, the *t*-test is conducted, as shown in Table 3. Although the *p*-value of the comparison method indicator was significant, it was significantly lower than that of the research method. The research method had more significant significance. After comprehensive verification, this research method performed the best among various comparison methods, verifying its practicality and effectiveness in voltage regulation.

The improvement of this research method on existing voltage regulation technology is mainly reflected in multiple dimensions such as theoretical basis, response speed, and robustness, as shown in Table 4. Overall, the research method has more significant performance advantages and can better adapt to the dynamic changes in voltage, ensuring the operational efficiency and stability of the smart grid.

5. Conclusion

In the smart grid, voltage regulation is a key link that ensures the stable operation of the grid and high-quality power supply. First, the smart grid is partitioned. Then, the MG is introduced to optimise and solve the voltage. From the results, the error value of the MG-AM method was within -0.8 $\times$ 10^{-4} –1.2$\times$$10^{-4}$. The IAE, ISE, ITAE, ITMSE, ISTAE, and ISTSE of the control method were 0.0051, 0.0056, 0.027, 0.00204, 5.13, and 0.00463, respectively. All error integration criteria results are lower than other commonly used voltage regulation methods. In specific case studies, the method based on MG-AM not only had a relatively stable and concentrated voltage distribution, but also tended to approach the reference value of 1.00 p.u. Its performance was superior to other methods. The output voltage fluctuation range of MG-AM was [0.99–1.03], and the cumulative energy utilisation efficiency was 0.83. The designed method can effectively regulate voltage, ensuring that all nodes can receive stable voltage during power transmission and distribution. It can also achieve network load balancing and control the direction of power flow.

This method combines MG and AM to focus on key information while ignoring irrelevant information to adapt to large-scale power grid demands, which has good scalability. The individual agents in MG make decisions based on local observation information, reducing reliance on global communication. The AM can further screen key information and reduce the amount of communication data. Therefore, the combination of the two can effectively improve communication robustness. In this model, if the parameter settings are not reasonable, it may lead to decision-making errors by the intelligent agent and affect the voltage control effect. Therefore, the study accurately estimates the action function and evaluation function through a large amount of historical data and real-time

Table 3
Statistical Significance of Evaluation Indicators

Methods	MG-AM		DNN		PID		RP	
Evaluation indicators	t	p	t	p	t	p	t	p
MAE	5.32	0.001	6.27	0.02	6.75	0.01	3.08	0.002
IAE	6.87	0.001	5.86	0.01	5.86	0.02	2.53	0.003
ISE	4.29	0.001	4.02	0.01	5.43	0.03	6.15	0.001
ITAE	7.13	0.001	6.73	0.02	6.77	0.01	4.17	0.001
ITMSE	4.59	0.001	5.61	0.01	8.02	0.02	2.89	0.003
ISTAE	5.33	0.001	7.43	0.01	7.13	0.01	6.45	0.002
ISTSE	6.05	0.001	5.17	0.01	679	0.01	2.09	0.001

Table 4
Specific Improvements of Research Methods on Voltage Regulation

Dimension	Existing methods	MG-AM
Theoretical basis	PID control, traditional optimisation algorithm	MG+AM
Response speed	Dependent on sampling frequency or iteration performance	Update the status function in real-time
Robustness	Dependent on preset thresholds, delayed response to sudden faults	AM can monitor abnormal interference in real time
Extensibility	Relying on centralised control	Multiple intelligent agents make decisions simultaneously, and AM can adapt to different devices
Communication Efficiency	Dependent on broadband real-time communication	Local observation combined with key information can reduce unnecessary communication consumption
Parameter adaptability	Fixed parameters, difficult to adapt to dynamic changes in voltage	Dynamically update state transition probability and attention weight parameters

monitoring data, and updates them regularly to ensure the reliability of the model.

However, there are still shortcomings in the research. In subsequent research, for emerging energy smart grids, the impact of external conditions such as lighting conditions on the voltage environment needs to be considered to optimise the performance of this voltage control method. In addition, this method can be applied to cross regional voltage coordination control, achieving collaborative decision-making between regions through MG theory, while using AM to focus on key information in each region, improving the efficiency and stability of cross regional voltage control.

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Biographies

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