DOI 10.24425/aee.2024.150888

Research on optimal scheduling strategy of source-grid-load-storage in rural low-voltage distribution network

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(Received: 18.12.2023, revised: 22.08.2024)

Abstract: The increasing demand for centralised power consumption in rural agriculture may result in low voltage and three-phase imbalance issues at the end of the distribution network. Furthermore, the extensive implementation of distributed photovoltaic (PV) systems may cause an imbalance between agricultural power load and PV output, exacerbating the issue of PV losses. In this paper, an optimal scheduling strategy for an integrated source-network-load-storage system is proposed to solve the above problems. The proposed strategy involves a dispatch model that includes PV power generation and energy storage, with the objective of maximising PV consumption and minimising operating costs. The PPO algorithm is finally employed to solve the cooperative optimisation model for source-grid-load-storage. The proposed scheduling strategy has been validated through examples, and the results demonstrate its effectiveness in ensuring the economic and safe operation of rural distribution networks.

Key words: energy scheduling, optimal scheduling strategy, PPO, rural low-voltage distribution network, source-grid-load-storage integrated system

1. Introduction

With the economic and social development, the scale of electricity consumption in China's rural areas is gradually increasing. Industrial and agricultural production as well as power consumption for daily living are increasing day by day, leading to growing requirements for the quality of electrical energy [1]. Rural agriculture requires three-phase power to support livestock breeding, vegetable greenhouses, and agricultural product processing. However, some rural areas only have access to a two-phase, two-wire power supply with a long radius, resulting in low voltage and poor power quality at times, which fails to meet the users' electricity requirements. The issue of low voltage has been identified. Low voltage not only affects the normal use of electricity by users but also increases power loss in the grid, which impacts the secure operation of the power system and the functionality of power supply [1]. Rural areas are distinguished by evident seasonal variations, low voltage, imbalanced three-phase power, and significant network losses. Low voltage and imbalanced three-phase power are the primary factors that cause power quality issues in the station area. The fundamental cause of low voltage is the insufficient power supply capacity at the grid terminal. To address this issue, it is necessary to analyze the operating characteristics of the station transformer. It is important to note that pure transmission and distribution alone cannot solve this problem [2]. In recent years, researchers and scholars have increasingly recognized the potential of PV power generation and energy storage technologies to promote the sustainable development of rural power supply. These technologies can be applied in rural low-voltage distribution networks to resolve problems.

With the potential for large-scale PV power generation in rural areas, it is possible to satisfy one's own power demand through PV power generation. The integration of distributed PV equipment and the power grid enables the efficient use of solar energy. This is significant for promoting local consumption of distributed PVs and reducing line loss and transmission capacity occupation caused by large-capacity transmission [3]. However, PV power generation's instability and uncontrollability can affect the power system's stable operation. Accessing rural low-voltage distribution networks often leads to issues such as voltage fluctuations. From a different perspective, the swift advancements in energy storage technology present new opportunities for addressing power quality issues in rural low-voltage distribution networks. By combining a PV power generation system with an energy storage system, a source-grid-load-storage integrated operation model can be built. This allows for flexible management and optimal scheduling of electric energy, enhancing the efficiency of electric energy utilization and bolstering power grid stability. To optimize the operation of rural low-voltage distribution networks and maximize the benefits of PV power generation and energy storage systems, traditional optimization scheduling methods may not suffice. In this context, deep reinforcement learning algorithm becomes a novel and effective solution. The deep reinforcement learning algorithm has the ability to learn the optimal scheduling strategy by interacting with the environment, resulting in intelligent and optimized scheduling of the integrated source-grid-load-storage system [4]. The integrated source-grid-load-storage system facilitates the utilization of clean energy in rural areas and promotes the efficient utilization of resources. It is an important part of the new power system and plays a crucial role in expediting the achievement of the carbon peaking and carbon neutrality goals.

Currently, literature [5] proposes optimizing the scheduling of integrated source-grid-load-storage systems, with a focus on rural areas. The coordination of source-grid-load-storage is optimized, taking into account integrated demand response and the role of biogas systems in enhancing energy utilization efficiency. Additionally, the carbon emission costs associated with the system are considered, with the aim of enhancing carbon reduction benefits. Literature [6] proposes a two-phase energy scheduling strategy for an off-grid wind-grid storage-coupled hydrogen production system. The strategy responds to the impact of uncertainties in power source and load demand variations on the optimal scheduling of the system. It achieves the best system stability through day-ahead-intraday coordinated optimization. In accordance with the dual-carbon objective, Literature [7] formulates constraints and develops a wind-solar storage-based power system. The coordinated planning model of the source-grid-load-storage is used to determine power generation planning and the optimal allocation scheme of the storage energy. Literature [8] addresses the issues of spatial and temporal differences in loads in rural areas, as well as the uneven distribution of loads overall. The first multi-station area flexible DC interconnection system was constructed to address challenges such as load transfer after power outages, difficulty in securing emergency power supply, and the demand for clean energy consumption across station areas. Literature [9] proposes the low-voltage DC distribution method to optimize the utilization of PV power generation in rural areas, considering the limitations of traditional distributed generation and the rural distribution network. This method enables flexible interconnection of distribution substation areas.

To address the challenges posed by the integration of renewable energy sources, such as wind power, many scholars have conducted research on dispatch planning for a new type of electric power system that can handle the increased stochasticity and uncertainty. Literature [10] constructs a model that includes the generation, utilization and synergy with storage of renewable energy sources. Literature [11] based the objective function on the maximum utilization of renewable energy during the planning period. Literature [12] proposes an integrated planning method for source-grid-load-storage taking into account flexibility by considering the possible impacts of different capacities and locations of energy storage on grid planning.

The objective of this paper is to examine power quality issues, such as low voltage and three-phase unbalance, which are frequently encountered at the end of low-voltage distribution networks in rural areas. This paper proposes the construction of an integrated source-grid-load-storage system in rural low-voltage stations. It establishes a new research framework and mathematical model for power system generation planning that considers the coordinated optimization of source-grid-load-storage under the dual-carbon objective [13]. To solve the optimal strategy of system optimal dispatch for the corresponding planning period, PPO algorithm is employed.

2. Integrated system architecture of source, grid, load, and storage for low voltage distribution networks in rural areas

2.1. Western rural LV distribution network source-grid-load-storage integration system structural framework

The object studied is a rural 10 kV LV distribution network in the west. The rural distribution network has natural stratified and radial characteristics, and the rural distribution network consists of 10 kV/0.4 kV transformers covering rural LV supply stations. The structure of rural microgrid system in Huining County, Gansu Province, which is dominated by agricultural loads, is shown in Fig. 1. The region is vigorously developing animal husbandry, vegetable greenhouses and agricultural product processing. The peak load of equipment used in agricultural production occurs in June, and the power consumption load of the farming industry shows a steady trend throughout the year. This paper aims to optimise the operation of rural distribution networks at the 10 kV level by constructing a source-grid-load-storage integrated system at the end of the distribution network. At the same time, by using tariff compensation to coordinate the power of decentralised power sources, to guide the agricultural load for a reasonable transfer, to ensure the economic viability and secure operation of rural distribution networks.

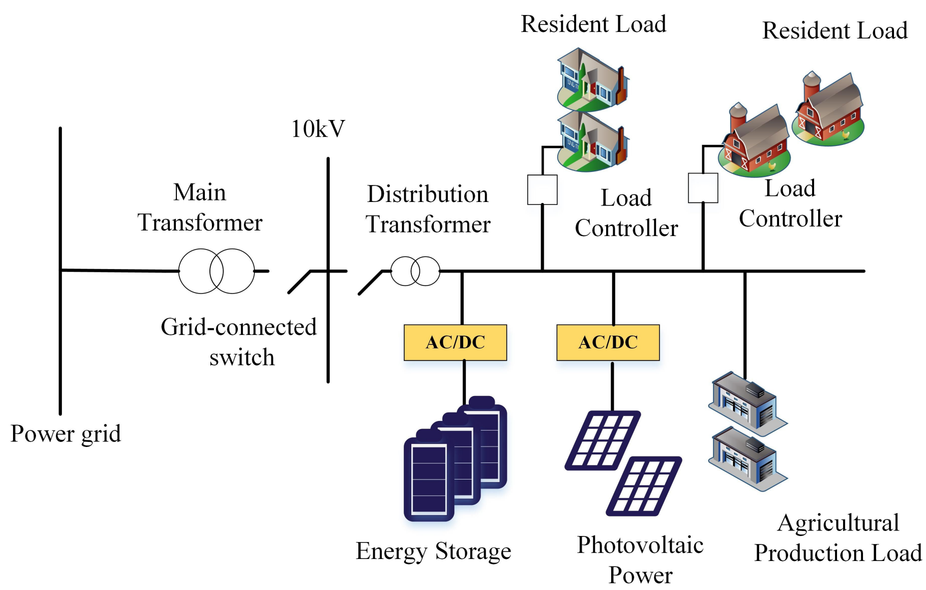

Fig. 1. Rural low-voltage power supply area system structure diagram

This paper proposes an integrated microgrid co-optimisation architecture for source-grid-load-storage integrated microgrids in rural western China. The primary aim is to meet the demand for rural electricity by maximizing the use of PV power generation and selling excess PV power to the grid for revenue. The basic framework of source-grid-load-storage integrated microgrid operation is shown in Fig. 2. It mainly includes distribution grid, PV, renewable energy, energy storage, rural agriculture, rural livestock and residential electricity loads. Energy storage, the use of power and

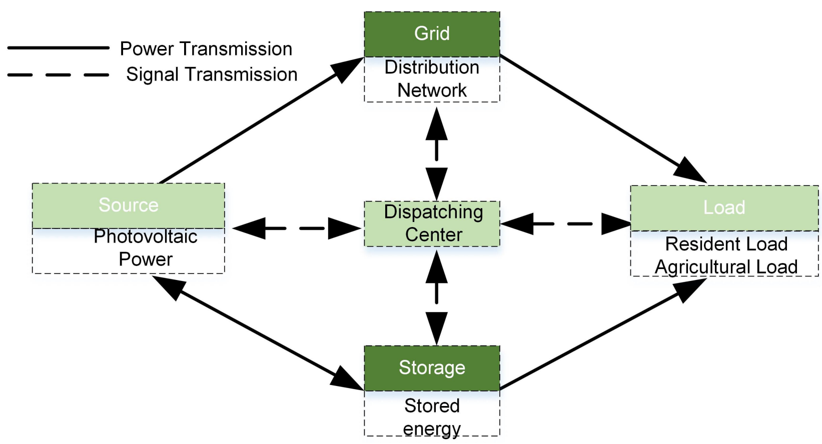

Fig. 2. Basic framework for the operation of rural source-grid-load-storage integrated microgrids

heat storage devices to achieve energy supply peak shaving and valley filling, and improve the efficiency of energy utilization; energy utilization, i.e., direct energy supply to the demand nodes of electricity, heat and gas loads. On the source side, it is mainly distribution grid and distributed PV. On the load side, it mainly focuses on daily electricity consumption in rural areas as well as animal husbandry and agriculture. On the storage side, it considers electric energy storage, and on the network side, it is connected to each other through the power grid.

2.2. Optimized scheduling strategy for integrated source-grid-load-storage system in western rural distribution network

The primary objective of the cooperative optimization architecture for "source-grid-load-storage" is to maintain a balance between the energy supply and user sides within the microgrid. The system optimization strategy aims to achieve self-consumption of PV power generation and maximize its usage [13]. The adjustable unit's basic parameters are inputted to initialize the optimization algorithm. Simultaneously, forecast data for PV power generation and load profiles are also inputted. During peak generation, the flexible load is shifted to maximize the consumption of PV output and reduce the PV curtailment ratio. Any surplus PV output is absorbed by the energy storage and used during the valley of the PV output to smooth out the peak-valley difference. The optimization model is created based on the objective function and constraints, and solved using deep reinforcement learning.

3. Optimal scheduling model for rural source-grid-load-storage-integrated microgrid stations with PV

The system considered in this paper consists of PV, energy storage and loads by connecting to the grid and developing an optimal scheduling strategy to minimize operating costs with maximum PV consumption.

3.1. Equations

PV power generation model

The project is located in the central part of Gansu Province, between 35°24′ – 36°26′N and 104°29′ – 105°31′E. The terrain is tilted from southeast to northwest, with rolling hills and ravines. It is a temperate semi-arid climate. The region experiences an annual precipitation of 267.1 mm and an average temperature of 9.2°C. The extreme maximum temperature recorded annually is 34°C, while the extreme minimum temperature is –23.3°C. The average ground temperature is 12.4°C, and the frost-free period lasts for 154 days each year. Additionally, the region receives an average of 4.51 hours of sunshine per day. The total annual radiation in the site area is 1646.8 kWh/m^2. Solar energy resources are abundant.

The output of PV systems can be affected by various uncertain factors, such as light intensity, radiance, season, weather conditions, and geographical location. The light in rural areas is sufficient, the output in spring and summer is large, and the output in autumn and winter is small. The PV output is modelled as shown in Eqs. (1) and (2).

$$\begin{cases} 0 \le P_t^{\mathrm{PV}} \le P_t^{\mathrm{PV0}} \\ Q^{\mathrm{PV,min}} \le Q_t^{\mathrm{PV}} \le Q_t^{\mathrm{PV,max}} \end{cases}, \tag{1}$$

$$\begin{cases} Q^{\mathrm{PV,max}} = \sqrt{\left(S^{\mathrm{PVinv}}\right)^2 - \left(P_t^{\mathrm{PV}}\right)^2} \\ Q^{\mathrm{PV,min}} = -\sqrt{\left(S^{\mathrm{PVinv}}\right)^2 - \left(P_t^{\mathrm{PV}}\right)^2} \end{cases}, \tag{2}$$

where P_t^{PV0}, P_t^{PV}, Q_t^{PV} represent the full output power, the active power on the grid, the reactive power of the PV system at time t. S^{PVinv} denotes the corresponding inverter capacity of PV power generation. $Q^{\mathrm{PV,max}}$ and $Q^{\mathrm{PV,min}}$, represent the upper and lower bounds of the reactive power support provided by the system.

Energy storage device model

The energy storage referred to in this article is an energy storage battery, the device regulates peaks and valleys and is widely used in optimizing power system scheduling. This plays a significant role in facilitating the utilization of renewable energy sources and improving the active support capacity of new energy. During times of peak power consumption, the stored electricity in the energy storage will be released to even out the fluctuations in the load. Conversely, during times of low power consumption, the energy storage will act as a load and charge by storing electricity. The energy storage is generally in two states, charging or discharging, and generally use the charge state of charge (SOC) measurement. The battery energy storage system is modelled as shown as below.

When charging a battery, the state of charge at time $t + 1$ can be expressed as (3).

$$\mathrm{SOC}_{t+1} = \mathrm{SOC}_t\,(1 - \delta_t) + \frac{P_{B,t} \cdot \eta_c \cdot \Delta t}{C_B}, \tag{3}$$

$$P_{B,t} = \varphi \cdot I_{B,c} \cdot V_{B,c}. \tag{4}$$

When the battery is discharged, the state of charge at time $t + 1$ can be expressed as (5).

$$\mathrm{SOC}_{t+1} = \mathrm{SOC}_t\,(1 - \delta_t) - \frac{P_{B,t} \cdot \Delta t}{C_B \cdot \eta_B}, \tag{5}$$

$$P_{B,t} = \varphi \cdot I_{B,d} \cdot V_{B,d}, \tag{6}$$

where: δ_t denotes the power loss coefficient, and the average value is 0.0002, η_c is the charging efficiency, and η_B denotes the discharge efficiency. SOC_{t+1} denotes the state of charge at time $t + 1$ when the battery is charging or discharging at time period t; Δt denotes the charging and discharging time interval. $P_{B,t}$ denotes the power of charging and discharging of the battery, and the unit is kW. φ is the power factor. $I_{B,c}$ denotes the charging current, and $I_{B,d}$ denotes the discharging current, and $V_{B,c}$, $V_{B,d}$ denote the charging and discharging voltage, respectively. C_B denotes the rated capacity of the battery, the unit is kWh.

Load characterization

Influenced by the country's economic development, rural electricity consumption shows a continuous growth trend. Requirements for power quality have also risen gradually. Rural loads generally include residential loads, planting agricultural power loads, breeding agricultural power loads and public facilities loads.

Agricultural production operation load

According to research, after the construction of new rural areas, the power consumption of rural agricultural production gradually shifts to scale. The agricultural power facilities involved in this shift include irrigation equipment, greenhouse watering machines, drainage systems, and harvesting equipment. Irrigation load node j at the configuration of the same parameters of irrigation facilities and reservoirs, irrigation facilities can be flexibly adjusted in terms of operation time and work intensity, belonging to the flexible load.

Residential load

The electricity consumption equipment used by rural residents mainly comprises various household appliances, air conditioners, and lighting. The residential load is generally larger from seven to eleven o'clock in the evening, with a significant peak. Residential load is also affected by the weather, in the summer and winter electricity consumption, the maximum load generally occurs in June-August, and the residential layout of the residents show a trend of concentration, which requires high power quality.

In rural areas, loads can be classified as either rigid or flexible based on their characteristics. Flexible loads are controllable and can be adjusted to meet the regulatory requirements of the power system. Typically, agricultural electricity consumption in rural areas falls under the category of flexible loads. Load curves are generated based on load data from pilot areas.

3.2. Objective functions

In this paper, the optimized operation of the system is aimed at PV to achieve self-generation and self-consumption, reduce the dependence on traditional energy sources, achieve a higher proportion of clean energy supply, minimize the operational expenses of the system, and improve the quality of power [14]. The objective function is based on the best economy, while considering the discard rate, network loss, energy storage, PV output, and node voltage as constraints.

1. Operating cost

$$\min F_1 = C^{\mathrm{PV}} + C^{L\mathrm{loss}} + C^{DS} + C^{ES} + C^{GS}, \tag{7}$$

where: F_1 is the objective function, C^{PV} is the PV scheduling cost, $C^{L\mathrm{loss}}$ is the network loss cost, C^{DS} is the flexible load scheduling cost, C^{ES} is the energy storage cost, and C^{GS} is the power grid purchase cost.

$$\begin{cases} C^{\mathrm{PV}} = \sum\limits_t c^{\mathrm{PV}} P_t^{\mathrm{PV}} \\ C^{L\mathrm{loss}} = \sum\limits_t \sum\limits_{ij\in E} c^{\mathrm{loss}} r_{ij} l_{ij,t} \\ C^{DS} = \sum\limits_t c^{DS} P_t^{DS} \\ C^{ES} = \sum\limits_t c^{ES} P_{B,t} \\ C^{GS} = \sum\limits_t c^{GS} P_t^{GS} \end{cases} . \tag{8}$$

In the formula, C^{loss}, C^{PV}, C^{DS}, C^{ES} and C^{GS} are network loss penalty cost, unit PV scheduling cost, flexible load scheduling cost, energy storage scheduling cost and power grid purchase cost. r_{ij} represents the resistance of the branch, and $l_{ij,t}$ represents the square of the current of the branch ij at time t. P_t^{DS} and P_t^{GS} are the power of flexible load participating in scheduling and the power purchased by the power grid at time t, respectively.

2. PV consumption rate

$$\max F_2 = \begin{cases} 0 & P_t^{\mathrm{PV}} = 0 \\ \dfrac{P_t^{\mathrm{PV}}}{P_{B,t} + P_t^l} \times 100\%, & 0 < P_t^{\mathrm{PV}} \le P_t^{\mathrm{PV0}} \end{cases}, \tag{9}$$

where P_t^l is the power generation consumed by the energy storage and load at time t.

3.3. Constraints

The constraints of the objective function of the source-grid-load-storage integrated microgrid system include the node voltage, unit output, energy storage charge, line current load, and overall power balance constraints.

1. PV constraints
   A significant penetration of PV systems into the distribution network can affect the overall stability of the distribution grid, so the output power should be taken into account when reconnecting the PV [15].
   $$0 \le P_t^{\mathrm{PV}} \le P_t^{\mathrm{PV0}}. \tag{10}$$
2. Flexible load restraint
   $$P_n^{\min} \le P_n^t \le P_n^{\max}, \tag{11}$$
   where: P_n^t denotes the output power of the flexible load at time t, $P_n^{\min}$ and $P_n^{\max}$ denote the upper and lower limits of the demand power of the flexible load.
3. Energy storage charge constraints The regulation of power system peaks and valleys can be achieved through the charging and discharging of energy storage. However, it is important to consider the impact of the frequency and depth of these cycles on the lifespan of the energy storage. Therefore, constraints on the charge state and power of the energy storage are necessary.
   $$\begin{cases} \mathrm{SOC}_{\min} < \mathrm{SOC}\,(t) < \mathrm{SOC}_{\max} \\ P_{B,c}^{\min} \le P_{B,t} \le P_{B,c}^{\max} \\ P_{B,d}^{\min} \le P_{B,t} \le P_{B,d}^{\max} \end{cases}, \tag{12}$$
   where: $\mathrm{SOC}_{\min}$, and $\mathrm{SOC}_{\max}$ denote the minimum charge state and maximum charge state of the energy storage, respectively; $P_{B,c}^{\min}$, $P_{B,c}^{\max}$, $P_{B,d}^{\min}$ and $P_{B,d}^{\max}$ are the upper and lower limits of the charging and discharging power within the system.
4. Power balance constraint
   $$P_{f,t} = P_t^l + P_t^{\mathrm{PV}} P_{B,t}, \tag{13}$$
   where $P_{f,t}$ is the unit electric power at time t.
5. Node voltage constraint
   $$U_{i,t}^{\min} < U_{i,t} < U_{i,t}^{\max}, \tag{14}$$
   where $U_{i,t}^{\min}$ is the node voltage of node i at time t, and $U_{i,t}^{\max}$, $U_{i,t}^{\min}$, respectively, are the maximum and minimum voltage limits of node i at time t.
6. Line current constraints
   $$I^{\min} < I < I^{\max}, \tag{15}$$
   where I is the line current, and $I^{\max}$, $I^{\min}$, respectively, are the maximum and minimum permissible line current.

4. Model solving

4.1. Model solving algorithm

Deep Reinforcement Learning has strong abstraction and representation capabilities, and is extremely advantageous in solving dynamic problems. By learning and analyzing historical load data, accurate load forecasting models are established to provide optimal distribution network planning schemes to adapt to the needs of rural areas. This paper solves the optimal scheduling model based on deep reinforcement learning algorithm.

1. Deep reinforcement learning (RL) elements

   RL can be represented by Markov Decision Process (MDP), which is the basis of reinforcement learning [16]. Firstly, the mathematical framework of transforming the mathematical form of the optimal scheduling model into MDP is given, which is represented by a five-tuple:

   $$< S, A, P, R, \gamma >.$$

   Among them, S symbolizes the observable state available to the agent, A represents the action taken by the agent. R is the real value, represents the reward function, P represents the set of state transition probabilities, and γ is the discount factor.

   The state in this paper includes PV output, load power consumption, energy storage state of charge, the previous action value and the current period, and the action space includes energy storage charge and discharge. The reward function is transformed by the objective function. Learning and decision makers are called agents, and the interacting component with the agents is commonly referred to as the environment. The agent engages in ongoing interactions with the environment. This interaction process can be seen as multiple moments. At each time step, the agent chooses an action based on the current state of the environment and a specific strategy. and the environment selects the next action according to the transition probability. A trajectory can be defined as a sequence of states, actions, and rewards, often represented as:

   $$\tau = (S_0, A_0, R_0, S_1, A_1 R_1, \ldots). \tag{16}$$

   The trajectory τ serves as a recording of the interactions between the agent and the environment. The initial state of the trajectory is obtained by randomly sampling from the distribution of initial states. A trajectory, also referred to as an episode or a round, represents a sequence that starts from the initial state and continues until reaching the terminal state [17]. Exploration refers to the agent through the interaction with the environment to obtain more information, and the use refers to the use of the current known information to make the agent 's performance to achieve the best. Therefore, the balance of exploration and use of the two, in order to achieve long-term return (Long-term Return) is a very important issue in reinforcement learning.

   The benefits of MDP are related to the state and reward, and each step will get different results. The total benefits are composed of the instantaneous reward of the current state and the memory experience reward. Memory experience reward according to the experience of the training after the occurrence of a movement to determine how to get a greater reward. The instantaneous reward is obtained by taking action in the current state. It can be expressed as in Eq. (17):

   $$R = \sum_{t=1}^{T} (s_t, a_t) \, . \tag{17}$$

Reinforcement learning approaches can be categorized into two main types: those based on value functions and those based on policy functions. Among them, strategy-based reinforcement learning directly selects the action strategy through the learning strategy itself. Policy-based reinforcement learning uses parameterized probability distribution $\overline{\pi} = P(a \mid s;\, \theta)$ replaces the deterministic strategy $\pi(a \mid \boldsymbol{S})$ in reinforcement learning based on value function, and samples different actions in the returned action probability list.
Policy is used to describe the way in which agents take actions according to environmental observations. Policy is a mapping from a state and action to the probability distribution of the action [18], which is the probability of taking action a under state s.
The state and benefit after taking the action at are only related to the current state and action, and have nothing to do with the historical state. Decision is reflected in each state s, according to the state selection to make decisions to take action, through a set of parameters to parameterize the strategy, and through the neural network to optimize the parameters.

2. PPO algorithm
PPO is a strategy-based neighbor search reinforcement learning algorithm, which is used to make decisions in problems with complex state space and action space. The main idea is to use greedy strategy to update the strategy while maintaining the stability of the strategy. The efficiency of the strategy is improved by updating the strategy, and the strategy is updated by the gradient descent method, so that the strategy is explored many times in the environment. PPO uses a technique called "nearest neighbor search", which can limit policy updates to a small area, thus avoiding large jumps in policy. Different from the on-line strategy training data obtained by the current agent interacting with the environment, PPO finds $\overline{\pi.}(a \mid \boldsymbol{S})$ to replace $\pi(a \mid \boldsymbol{S})$ to complete the interaction with the environment based on the off-line strategy. The core of the algorithm is to update the policy gradient and push out different network parameter update methods.

4.2. Model solving process

When using PPO algorithm to solve the model, the objective function of the model and the definition of the problem are first clarified. The algorithm flowchart is shown in Fig. 3. In this paper, the minimum operating cost and the maximum PV consumption rate are taken as the objectives. The agent first initializes the algorithm, and defines the state of the system at time t as vector s, including the cost of energy, the state of charge of energy storage, the cost of purchasing electricity, and the load condition. The mathematical expression is converted into a framework for reinforcement learning. The state space and action space of the problem are determined. The state space includes information such as load, power supply and system topology. The action space refers to the operation that can be taken, which is carried out by controlling the switching state of the power supply and adjusting the charging and discharging of the energy storage device. According to the system parameter setting environment model, it is used to interact with the current state and observe the current state of the system, including the requirements, energy supply, energy storage system status, etc. According to the state space and action space of the problem, the neural network structure required by the PPO algorithm is designed. Usually, deep neural networks are used as policy networks to learn decision strategies. The appropriate number of network layers, activation function and output layer structure can be selected. Initialize the strategy π and the value function V, and set the reward evaluation index to improve the strategy network during the training process. After the strategy network training is completed, it is applied to the integrated optimization problem of source-grid-load-storage at the end of rural low-voltage distribution network. According to the current state, the operation strategy of the power grid is adjusted by the action of the policy network output to achieve the optimization goal.

1. Collect experience Expi for each trajectory, including state s, action a and reward r. At time t, the agent receives the observed running state from the environment, transmits the action to the environment, and updates itself accordingly. According to this information, the optimal action is selected to adjust the output of the equipment.
2. Calculate the reward function $A = Q(s, a - V(s))$. During the training process, the agent learns the best strategy through trial and error and reward mechanisms. After the agent takes a specific action and observes the feedback of the system, it updates its strategy network based on the reward or punishment of the feedback to optimize its decision-making process.
3. The proxy target $\overline{\pi}\,(a\,|\,\boldsymbol{S})$ is calculated to complete the update policy gradient.
4. Use neighbor search to update the strategy.
5. Update value function V.
6. Repeat 2–6 until convergence.

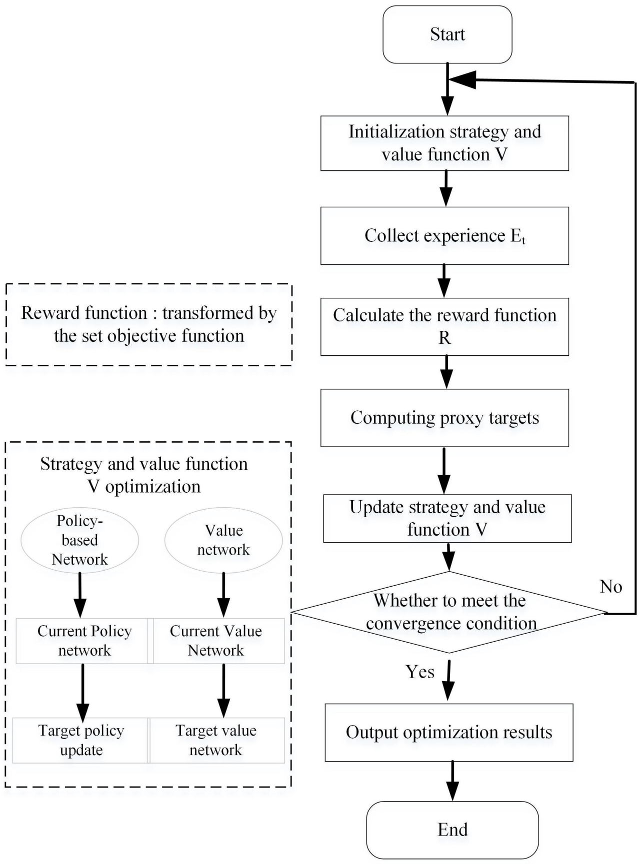

Fig. 3. Flow chart of optimal scheduling strategy based on PPO

5. Case analysis

5.1. Data processing

Taking the rural source-grid-load-storage integrated system in a certain area of western China as the research object, the optimal scheduling is carried out according to the annual predicted light and electricity load demand in the area. Among them, the capacity of the station area is 50 kVA, the PV construction capacity is 10 kW, and the area is 80 square meters. The energy storage construction capacity is 50 kWh. The PV output is set to 0.95, and the charging and discharging power of the energy storage is set to 0.9. The demand of the rural source-grid-load-storage integrated system includes daily electricity consumption and agricultural load electricity consumption. Agricultural electricity can be used as a shiftable load to participate in scheduling. The power supply includes power grid and distributed PV power generation system. The time-of-use electricity price is set as Tables 1 and 2. The new energy power generation transaction price requires that the peak, valley, and flat transaction benchmark prices of new energy companies are the coal-fired benchmark price multiplied by the peak-valley time-of-use coefficient (peak-segment coefficient = 1.5, flat-segment coefficient = 1, valley-segment coefficient = 0.5). According to the meteorological historical data set and load data of the region, the training is carried out to predict the PV output curve and load forecasting curve of a certain day as shown in Fig. 4 and Fig. 5. Among them, the rural electricity load is divided into residential load and agricultural load. The residential load is regarded as the basic load, and the agricultural load is regarded as the shiftable load.

Table 1. Peak-valley period division of residential production users

Time division	Time	Electricity price (yuan)
Crest segment	7:00–9:00 17:00–23:00	0.6714
Flat section	23:00–00:00 00:00–7:00	0.4489
Valley section	9:00–17:00	0.2265

Table 2. Equipment parameters

Equipment name	Parameter	Numerical value
PV	Peak output (kW)	10
Stored energy	Rated capacity (kWh) System power (kWh) SOC_{min} SOC_{max}	50 30 0.1 0.9
Grid	Upper limit of power output (kW)	40

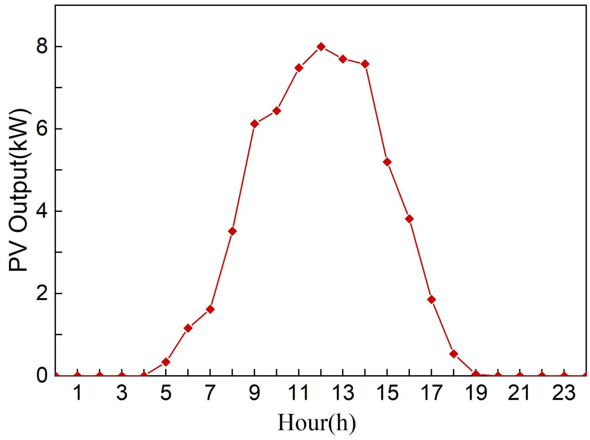

Fig. 4. PV output prediction curve

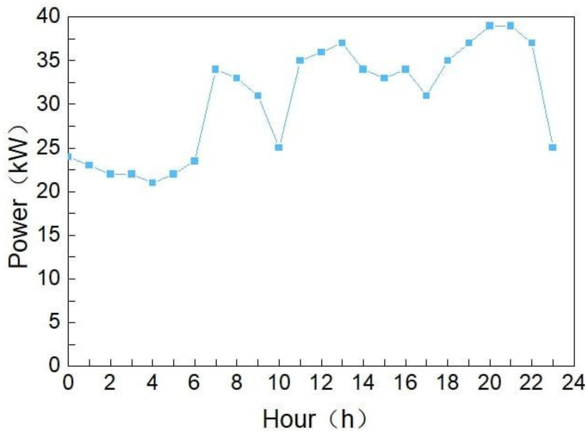

Fig. 5. Load power prediction curve

5.2. Analysis of scheduling results

PV, energy storage, and flexible load are added at the end, and collaborative optimization is performed through energy storage and flexible load scheduling. In order to verify the effectiveness of the proposed scheduling method, four scenarios are set to compare the scheduling results:

Scenario 1: Set Scenario 1 to do not consider energy storage access, flexible load does not participate in scheduling;

Scenario 2: Set Scenario 2 to consider energy storage access, flexible load does not participate in scheduling;

Scenario 3: Set Scenario 3 to do not consider energy storage access, flexible load participation in scheduling;

Scenario 4: Set Scenario 4 to consider energy storage access, while flexible loads participate in scheduling;

Among them, Scenario 1 is used as the control group and compared with the other three Scenarios. Through simulation calculation, the cost of dispatching results and PV consumption rate in four scenarios can be obtained.

The results are shown in Table 3. By analyzing the scheduling cost and comparing the situation of energy storage access in scenarios one and two, it can be seen that the operation cost is reduced and the PV consumption rate is increased in the case of energy storage access. Energy storage stores power at the peak of PV power generation and releases stored power at the valley. When storing electric energy, the PV consumption rate is increased. And the stored electric energy is released at the trough, which can reduce the cost of purchasing electricity from the power grid and realize the interaction between source and storage.

Table 3. Scheduling results of four scenarios

	PV consumption rate (%)	Operating cost (yuan)
Scenario 1	83.71	3 569.7
Scenario 2	86.3	3 116.3
Scenario 3	100	2 673.5
Scenario 4	100	2 113.7

Comparing the situation of flexible load in scheduling in Scenario 1 and Scenario 3, as shown in Fig. 6 and Fig. 7, considering the participation of flexible load in scheduling, it can be concluded that the flexible load participates in scheduling.

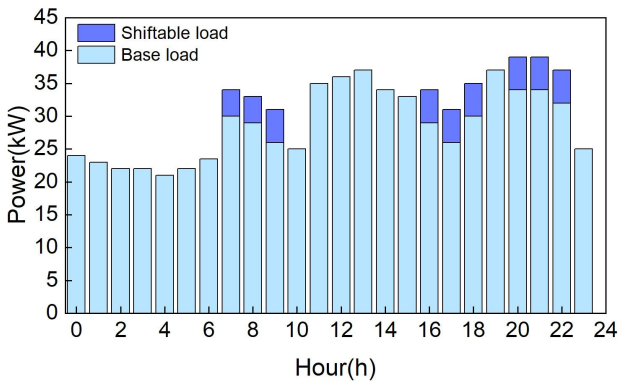

Fig. 6. Scene 1 load distribution

The electricity price of the shiftable load during the peak period of 7:00–9:00 can be transferred to the valley period of power grid purchase. Similarly, the shiftable load during 16:00–18:00 can be transferred to 0:00–3:00 to reduce peak purchase and increase the consumption rate of PVs. This maximizes the spontaneous use of PVs and reduces the operating costs of the system.

Compared to Scenarios 1 and 4, the participation of energy storage and flexible load in scheduling results in the highest PV consumption rate and the lowest operating cost among all

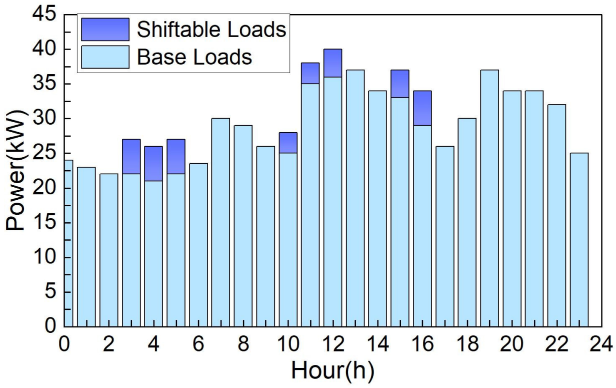

Fig. 7. Scene 3 load distribution

four scenarios. Collaborative scheduling allows flexible load electricity to avoid peak periods of electricity consumption, reducing the cost of electricity purchase and maximizing the consumption of PVs for efficient use of clean energy. At the same time, it can receive subsidies for electricity purchases, reduce costs, and integrate effectively with source-load-storage.

In summary, the collaborative optimization of the source-grid-load-storage integrated system is constructed at the end of the rural low-voltage distribution network. The good interaction of source-storage, source-load, source-load-storage is used to reduce the operation cost through energy storage access and flexible load participation. At the same time, the charging and discharging of energy storage and flexible load stabilize the peak and valley of PV output and increase the PV consumption rate.

5.3. Source-grid-load-storage system collaborative optimization analysis

Optimization analysis of low-voltage distribution networks has shown that incorporating energy storage and flexible load integration can effectively reduce operational costs, maximize user satisfaction, and achieve the maximum PV consumption rate. The optimal scheduling results are presented in Fig. 8. By optimizing the scheduling of the integrated source-grid-load-storage system, the operation strategy of energy storage can be obtained. During the day, when the output of the photovoltaic (PV) system exceeds the user's electricity demand, the excess electricity is stored by charging the energy storage system. This helps to improve the PV consumption rate and alleviate the problem of excess PV generation. When the PV output stops at night, the user's electricity consumption remains in the peak period. During off-peak and valley periods, the user's energy demand is met by purchasing electricity from the power grid, and the energy is stored in the energy storage. The stored energy is released by the energy storage for load utilization at the peak of the electricity price. The state of charge of energy storage is shown in Fig. 9.

The load scheduling results are shown in Fig. 10. The comparison of the curve before and after load transfer shows that the flexible load is shifted to the peak period of PV power generation from 10:00 to 14:00 in the morning and at night. This helps to alleviate the pressure of electricity consumption, increase the consumption of PV, and reduce the depth of charge and discharge of

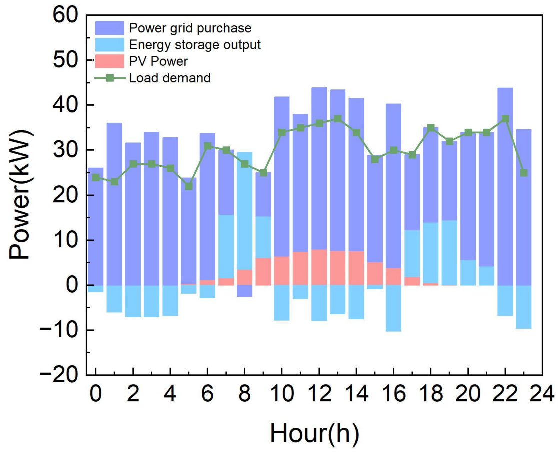

Fig. 8. Optimal scheduling results

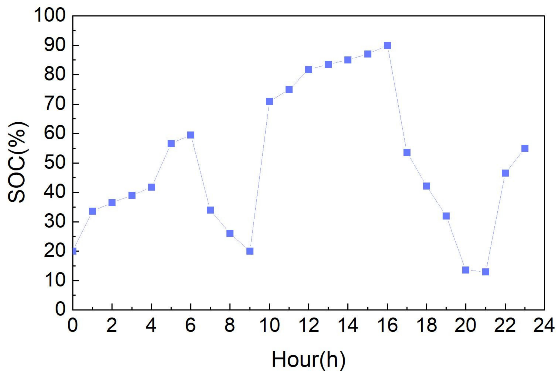

Fig. 9. State of charge of energy storage

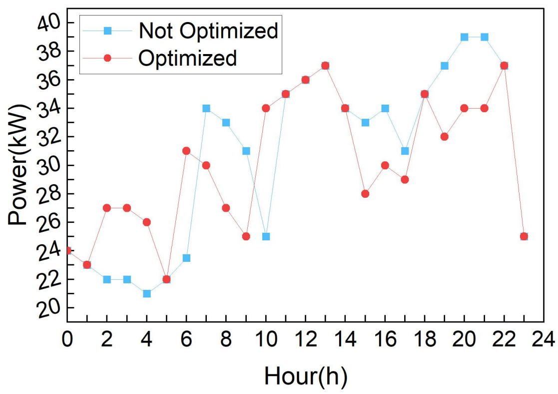

Fig. 10. Shiftable load optimization results

energy storage in coordination with energy storage. Additionally, this load transfer strategy enhances the lifespan of the energy storage system, resulting in an extended operational life. Furthermore, the transfer of flexible loads also contributes to peak shaving and valley filling within the system, effectively managing electricity consumption during high-demand and low-demand periods.

In summary, the proposed collaborative optimization model of source-grid-load-output integration at the end of rural low-voltage distribution network proposed in this paper can effectively reduce the operation cost and realize the complete consumption of PV through the interaction and coordination between source-grid-load-storage. By using the shiftable characteristics of flexible load, the shiftable load is transferred to the power purchase valley of the power grid. In peacetime, the energy storage charge and discharge are used for optimal scheduling to ensure the economic and reliable operation of the distribution network and effectively promote the consumption of new energy.

6. Conclusions

This paper examines the optimal scheduling model for the source-grid-load-storage of low-voltage distribution networks in rural areas of the West. It comprehensively considers the operational characteristics of rural power loads, PV power generation characteristics, system structure, and energy storage charging and discharging strategies. Simultaneously, economic factors such as operating costs and system income are considered when establishing an optimal scheduling model for rural low-voltage distribution networks based on deep reinforcement learning. The model takes into account the highest PV consumption rate and the lowest cost as operating objectives. The results demonstrate that:

1. Based on the operation data of low-voltage distribution network in a rural area, four typical scenarios are set up. The research results show that the collaborative interactive optimization strategy of source-load-storage can stabilize the peak-valley of PV output and realize the complete consumption of PV.
2. Based on the analysis of low-voltage distribution network, the optimal scheduling of source-grid-load-storage system is carried out. Through the translation of flexible load, the consumption rate of PV is increased, the depth of charge and discharge of energy storage is reduced, the service life of energy storage is increased, and the operating cost can be reduced by 40%.

The source-grid-load-storage integrated system can not only ensure the stable operation of the system, but also improve the PV consumption rate when connected to the grid. On the basis of ensuring the economic and reliable operation of the distribution network, it can effectively promote the consumption of new energy and improve the overall planning level of the distribution network. The proposed strategy also plays a positive role in improving the power supply reliability and power quality of the regional power grid.

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