Distributed Energy Resources Aggregation and Optimization Scheduling Model and Algorithm for Virtual Power Plants

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Abstract: With the ongoing energy transition and power system reform, Distributed Energy Resources (DERs) are playing an increasingly important role in modern power systems. DERs mainly include distributed photovoltaics, distributed wind power, small hydropower, biomass energy, fuel cells, and controllable loads, characterized by decentralized deployment and local consumption. The large-scale integration of these resources presents new opportunities and challenges for power systems. Effectively coordinating and managing these distributed energy resources has become a hot research topic.

Keywords: Virtual Power Plant (VPP); Distributed Energy Resources (DERs); Energy Storage Devices; Load Management

1. Introduction

The Virtual Power Plant (VPP), as a new energy management model, provides an effective solution for the coordination and optimization of distributed energy resources. VPP uses advanced information and communication technologies and control strategies to aggregate geographically dispersed and diverse distributed energy resources into a controllable and schedulable whole, enabling participation in power market transactions and system operations. VPP can not only improve the utilization efficiency of distributed energy resources but also provide flexible regulation capabilities for the power grid, enhancing system reliability and stability[1].

2. Existing Optimization Scheduling Models and Algorithms

For the optimization scheduling problem of VPP, scholars have proposed various models and algorithms. The main optimization objectives include:

Economic optimization: minimizing operating costs or maximizing economic benefits;

Environmental optimization: minimizing carbon emissions or maximizing the utilization of renewable energy;

Reliability optimization: maximizing system stability or minimizing load shedding probability;

Multi-objective optimization: comprehensively considering multiple objectives such as economic, environmental, and reliability.

In terms of modeling methods, commonly used ones include deterministic models, stochastic programming models, robust optimization models, and fuzzy programming models. Among them, stochastic programming and robust optimization models can better handle the uncertainty of DERs. In terms of solving algorithms, they are mainly divided into exact algorithms and heuristic algorithms. Exact algorithms such as linear programming, quadratic programming, and mixed-integer programming are suitable for relatively simple deterministic models; heuristic algorithms such as genetic algorithms, particle swarm optimization, and differential evolution algorithms are more suitable for solving complex nonlinear and non-convex optimization problems. In recent years, optimization algorithms based on artificial intelligence (such as deep reinforcement learning) have also been widely used in VPP scheduling, showing good performance[2].

3. Virtual Power Plant Model for Distributed Energy Resources Aggregation

3.1 Composition and Operation Mechanism of Virtual Power Plants

A Virtual Power Plant (VPP) aggregates and coordinates multiple Distributed Energy Resources (DERs) through advanced information and communication technologies, making them functionally equivalent to a conventional power plant[3]. The VPP comprises DERs, energy storage devices, loads, information communication systems, and control systems. The types of DERs are diverse, mainly including solar energy, wind energy, biomass energy, and small hydropower. These resources transmit their generation capacity in real-time to the control center via the information communication system. Energy storage devices store electrical energy during periods of low demand and release it during peak demand to balance supply and demand and improve energy utilization efficiency. Load management uses demand response technology to adjust loads, reducing peak loads and achieving a dynamic balance between supply and demand in the power grid.

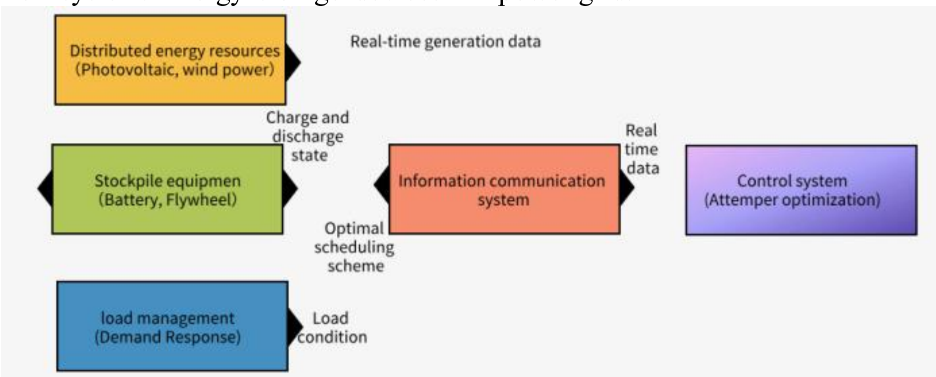

Figure 1. Overall System Layout

The operating mechanism of the VPP aims to achieve efficient utilization of DERs and stable operation of the power system through intelligent means. First, the information communication system monitors and transmits real-time generation data, storage status, and load conditions of various energy resources, providing comprehensive decision-making basis for the control system. Second, the control system optimizes scheduling based on real-time data and formulates the optimal dispatch plan. This plan comprehensively considers the characteristics of various energy resources, the status of energy storage devices, and load demands to achieve the goals of cost minimization, benefit maximization, and stable grid operation. In this way, the VPP not only improves energy utilization efficiency and economic benefits but also enhances the flexibility and reliability of the power system, contributing to the sustainable development of energy strategies.

3.2 Mathematical Description of the Energy Aggregation Model

To achieve the optimal scheduling of DERs, a mathematical model comprising the objective function and constraints needs to be constructed.

(1) Objective Function

Cost Minimization Objective Function:

$$\min Z=\sum_{t=1}^{T}\left(\sum_{i=1}^{N}C_i(P_{i,t})+\sum_{j=1}^{M}S_j(E_{j,t})+\sum_{k=1}^{L}D_k(L_{k,t})\right)$$

Where Ci(Pi,t)is the generation cost of the ith DER at time t, Sj(Ej,t)is the operating cost of the j-th energy storage device at time t, and Dk(Lk,t) is the demand response cost of the k-th load at time t.

Benefit Maximization Objective Function:

$$\max B=\sum_{t=1}^{T}\left(\sum_{i=1}^{N}R_i(P_{i,t})+\sum_{j=1}^{M}G_j(E_{j,t})\right)$$

Where Ri(Pi,t)is the generation revenue of the ith DER at time t, and Gj(Ej,t)is the discharge revenue of the j-th energy storage device at time t.

(2) Constraints

Power Balance Constraint:

$$\sum_{i=1}^{N}P_{i,t}+\sum_{j=1}^{M}E_{j,t}^{dis}-\sum_{j=1}^{M}E_{j,t}^{ch}=\sum_{k=1}^{L}L_{k,t}\quad\forall t$$

Where Pi,t is the generation power of the i-th DER at time t, Ej,tdis and Ej,tch are the discharge and charge power of the j-th energy storage device at time t, respectively, and Lk,t is the demand power of the k-th load at time t.

DER Output Constraint:

$$0\le P_{i,t}\le P_i^{max}\quad\forall i,t$$

Where Pimax is the maximum output of the i-th DER.

Energy Storage Device Operation Constraint:

$$E_j^{min}\le E_{j,t}\le E_j^{max}\quad\forall j,t$$

Where Ejmin and Ejmax are the minimum and maximum storage capacities of the jth energy storage device, respectively.

Load Demand Response Constraint:

$$L_k^{min} \leq L_{k,t} \leq L_k^{max} \quad \forall k,t$$

Where Lkmin and Lkmax are the minimum and maximum demand powers of the kth load, respectively.

The VPP optimization scheduling model for DERs aggregation is constructed through the above objective functions and constraints. This model comprehensively considers the generation cost and revenue of DERs, the operating cost and revenue of energy storage devices, the demand response cost of loads, and the power balance of the system, aiming to achieve cost minimization and benefit maximization. Meanwhile, the model also takes into account various constraints such as DER output, energy storage device operation, and load demand response, ensuring the feasibility and effectiveness of the optimization scheduling scheme[4].

In summary, the VPP optimization scheduling model for DERs aggregation effectively integrates and coordinates multiple DERs through information communication and control technologies, achieving efficient energy utilization and stable operation of the power system. The construction of the mathematical model and the design of the optimization scheduling algorithm can provide theoretical and technical support for realizing sustainable energy strategies.

4. Optimization Scheduling Model of Virtual Power Plants

4.1 Determination of Scheduling Objectives

The optimization scheduling objectives of a Virtual Power Plant (VPP) typically include cost minimization and benefit maximization. Cost minimization aims to reduce the operating costs of Distributed Energy Resources (DERs), the charging and discharging costs of energy storage devices, and the costs of load regulation.

The objective function can be expressed as:

$$\min Z = \sum_{t=1}^{T}\left(\sum_{i=1}^{N} C_i(P_{i,t}) + \sum_{j=1}^{M} S_j(E_{j,t}) + \sum_{k=1}^{L} D_k(L_{k,t})\right)$$

where Ci(Pi,t) is the generation cost of the i-th DER at time t, Sj(Ej,t) is the operating cost of the j-th energy storage device at time t, and Dk(Lk,t) is the demand response cost of the k-th load at time t.

Benefit maximization mainly focuses on the following aspects: first, the generation revenue of DERs, including electricity sales revenue and policy subsidies, which is one of the important income sources for DERs and directly affects their economic feasibility. Second, the discharge revenue of energy storage devices, which achieves profit maximization by discharging during peak demand periods to obtain higher electricity prices. This strategy not only optimizes the utilization rate of energy storage devices but also enhances overall economic benefits. Lastly, demand response revenue is obtained by adjusting loads for compensation. The demand response mechanism allows users to adjust their electricity consumption based on grid demand, thus reducing load during peak periods and obtaining corresponding economic compensation. The optimization and integration of these revenues help to enhance the overall benefits of the VPP, increasing its competitiveness and sustainability in the market.

The objective function can be expressed as:

$$\max B = \sum_{t=1}^{T}\left(\sum_{i=1}^{N} R_i(P_{i,t}) + \sum_{j=1}^{M} G_j(E_{j,t})\right)$$

4.2 Construction of Multi-Time-Scale Scheduling Models

The optimization scheduling of a VPP needs to consider scheduling problems on different time scales, including short-term, medium-term, and long-term scheduling. The scheduling objectives and constraints differ for each time scale.

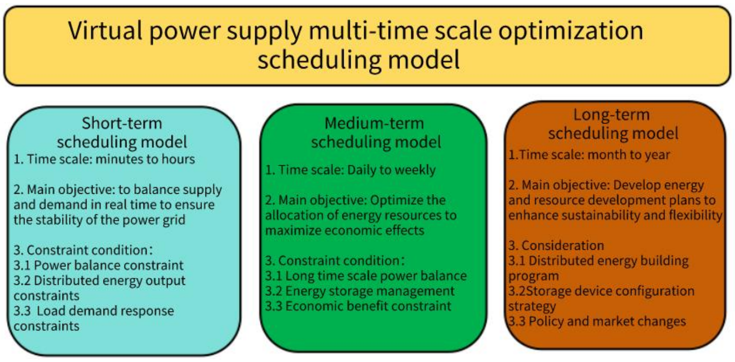

Figure 2. Multi-Time-Scale Optimization Scheduling Model of Virtual Power Plants

(1) Short-Term Scheduling Model
Short-term scheduling usually refers to minute-level to hour-level scheduling decisions. The main goal is to balance supply and demand in real-time to ensure the stable operation of the grid. The short-term scheduling model can be expressed as:

$$\min Z = \sum_{t=1}^{T}\left(\sum_{i=1}^{N} C_i(P_{i,t}) + \sum_{j=1}^{M} S_j(E_{j,t}) + \sum_{k=1}^{L} D_k(L_{k,t})\right)$$

Subject to:
Power balance constraint:

$$\sum_{i=1}^{N} P_{i,t} + \sum_{j=1}^{M} E_{j,t}^{dis} - \sum_{j=1}^{M} E_{j,t}^{ch} = \sum_{k=1}^{L} L_{k,t} \quad \forall t$$

DER output constraint:

$$E_j^{min} \le E_{j,t} \le E_j^{max} \quad \forall j,t$$

Energy storage device operation constraint:

$$E_j^{min} \le E_{j,t} \le E_j^{max} \quad \forall j,t$$

Load demand response constraint:

$$L_k^{min} \le L_{k,t} \le L_k^{max} \quad \forall k,t$$

(2) Medium-Term Scheduling Model
Medium-term scheduling usually refers to day-level to week-level scheduling decisions. The main goal is to optimize the allocation of energy resources to maximize economic benefits. The medium-term scheduling model can be expressed as:

$$\max B = \sum_{t=1}^{T}\left(\sum_{i=1}^{N} R_i(P_{i,t}) + \sum_{j=1}^{M} G_j(E_{j,t})\right)$$

Constraints are similar to those in short-term scheduling but need to consider power balance and energy storage management over a longer time scale.
(3) Long-Term Scheduling Model
Long-term scheduling usually refers to month-level to year-level scheduling decisions. The main goal is to formulate development plans for energy resources to enhance the sustainability and flexibility of the energy system. The long-term scheduling model needs to comprehensively consider the construction planning of DERs, the configuration strategy of energy storage devices, and the load growth forecast. The long-term scheduling model can be expressed as:

$$\max B = \sum_{t=1}^{T}\left(\sum_{i=1}^{N} R_i(P_{i,t}) + \sum_{j=1}^{M} G_j(E_{j,t}) - \sum_{i=1}^{N} C_i(P_{i,t}) - \sum_{j=1}^{M} S_j(E_{j,t})\right)$$

Constraints need to consider long-term resource planning and development strategies, as well as the impact of policy and market changes on scheduling.
By constructing multi-time-scale scheduling models, the optimal scheduling of DERs can be achieved on different time scales, improving the operational efficiency and economic benefits of the VPP, and ensuring the stable and reliable operation of the power system. In summary, the construction and optimization of the VPP scheduling model is an important approach to achieving efficient utilization of DERs. By comprehensively considering cost minimization, benefit maximization, and uncertainty factors, and constructing multi-time-scale scheduling models, strong support can be provided for the stable operation and sustainable development of the power system.

5. Design of Optimization Scheduling Algorithms

5.1 Algorithm Process Design

This study selects Genetic Algorithm (GA) and Deep Reinforcement Learning (DRL) as representative optimization scheduling algorithms, and designs their respective processes.

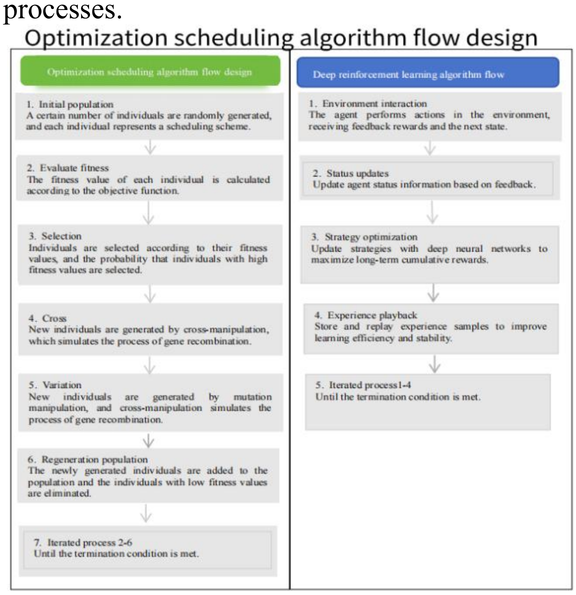

Figure 3. Optimization Scheduling Algorithm Process Design

The Genetic Algorithm (GA) is an optimization algorithm that simulates natural selection and genetic mechanisms, suitable for solving complex combinatorial optimization problems. Its basic process includes the following steps: In the population initialization phase, a certain number of individuals are randomly generated, each representing a possible scheduling solution.

Then, the fitness value of each individual is calculated based on a predetermined objective function, reflecting the quality of the individual scheduling solution. The selection operation is based on the fitness values, with individuals having higher fitness values being more likely to be selected, simulating the natural selection process. New individuals are generated through crossover operations, simulating gene recombination, thereby increasing population diversity and preventing premature convergence to local optima. Mutation operations generate new individuals by randomly changing some gene positions of the individuals, maintaining population diversity and further avoiding premature convergence. Finally, by updating the population, newly generated individuals are added to the population, and individuals with low fitness values are eliminated, maintaining the scale and quality of the population. By iterating these steps, the optimal solution is gradually approached until the preset termination conditions are met, such as reaching the maximum number of iterations or the fitness value no longer significantly improving.

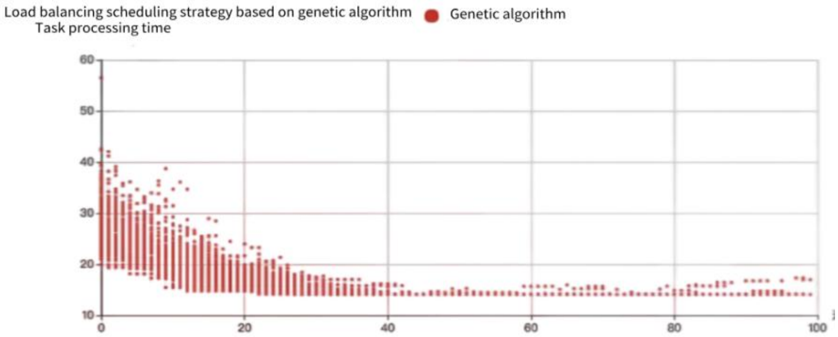

Figure 4. Load Balancing Scheduling Strategy Based on Genetic Algorithm

Deep Reinforcement Learning (DRL) combines deep learning and reinforcement learning techniques, suitable for handling complex dynamic optimization problems. Its process includes environment interaction, state update, policy optimization, and experience replay. The agent selects an action in the current state and interacts with the environment, which returns the corresponding reward and the next state based on the action. Based on the reward and new state feedback from the environment, the agent updates its internal state information, accumulates experience, and gradually learns the dynamic characteristics of the environment.

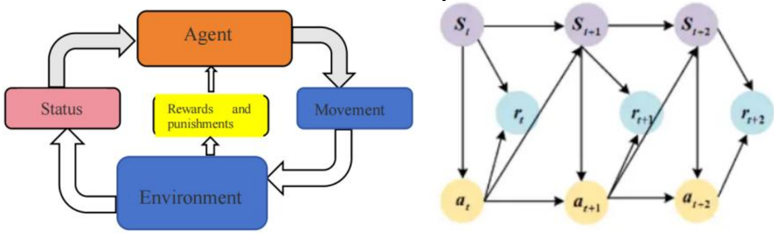

Figure 5. Feature Extraction Using Deep Neural Network (DNN)

The agent's policy is updated using a Deep Neural Network (DNN), with the objective of maximizing long-term cumulative rewards, thereby ensuring that the agent achieves maximum gains in future decisions.

5.2 Detailed Explanation of Key

The optimization process of the Genetic Algorithm (GA) includes multiple key steps, each of which has a significant impact on the quality of the final solution and the convergence speed. Deep Reinforcement Learning (DRL) combines the techniques of deep learning and reinforcement learning, suitable for complex dynamic optimization problems[5]. Its key steps include environment interaction, state update, policy optimization, and experience replay. The agent selects an action in the current state, interacts with the environment, and receives feedback in the form of rewards and the next state. The agent's experience samples, which include state, action, reward, and next state tuples, are stored and replayed. Experience replay helps to break the correlation between samples, improving learning efficiency and stability, and preventing the agent from overfitting to specific experiences. By repeatedly sampling from the experience replay pool for learning, the agent gradually improves the robustness and adaptability of its policy. These steps collectively form the optimization process of the DRL algorithm, enabling the agent to continuously learn and optimize scheduling strategies in complex dynamic environments, thereby achieving optimal performance.

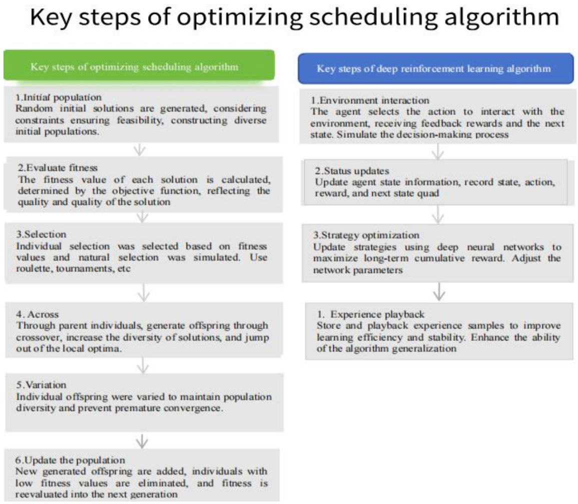

Figure 6. Key Steps of the Optimization Scheduling Algorithm

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