# DISPATCH METHOD OF LOAD-SIDE RESOURCES IN COUNTY POWER GRIDS WITH HIGH PROPORTION OF NEW ENERGY ACCESS

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*This paper constructs an interactive active distribution network architecture to get a real-time power system state. It uses a multi-time scale coordinated optimization process and builds physical models for new loads. Applying a genetic algorithm solves the system's optimal state, obtaining the global optimal solution and reducing shear load and wind and light abandonment. It cuts power system costs, boosts the economy, adapts to diverse loads, and expands scenarios.*

**Keywords**: Power system; optimal control method; active distribution network; flexible load interaction

## 1. Introduction

As contemporary power systems evolve, the load types in distribution networks gradually show a diversified development trend. However, the access to these new loads brings new challenges. Because of the randomness and volatility of clean energy itself, it brings greater peak load pressure to the distribution network, and these phenomena force us to consider whether the system is safe or not.

Given that power grid management must account for numerous variables, its dispatching strategy often needs to have a certain degree of flexibility, which is convenient to leave enough margin [1,2]. Ionescu et al. considers the elastic scheduling problem of microgrids. [3]. Ghinea et al. considers the economy and absorption rate of introducing renewable energy into the power system. [4]. A study introduced a real time collaborative control technology for wind power and load [5], and Ganesan and Ashfaq et al. proposed a control strategy involving an energy storage system [6,7]. Jain and Agarwal considered the access of distributed power supply and flexible load [8]. However, these control methods are only issued by the control center one-way dispatch instructions, with the challenge faced by control centers in accurately monitoring the system's operational status in real time [9,10]. With the development of artificial intelligence, some advanced control algorithms

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have gradually entered the field of distribution network operation management. By introducing neural networks and genetic algorithms [11, 12], Begum et al. can effectively capture complex patterns in time series data and improve the accuracy and reliability of prediction [13]. Chan et al. attempt to find the optimal solution by using SOCP [14]. However, these processing methods sacrifice high precision criteria, so finding a simpler and efficient solution algorithm is a problem that needs to be solved [15, 16].

In addition, current research on the characteristics of various distributed resources is insufficient, and the construction of relevant models is relatively simple. The studies by Zahraoui et al. and Joo & Choi et al. set the proportion of participating response load at a fixed proportion and the influences of energy storage and other factors were not considered [17,18]. This makes it difficult to meet the accuracy requirements when analyzing the distribution network [19,20]. In response to these challenges, this study proposes an optimized control strategy for active distribution networks that incorporate flexible load interaction. A load side control model is given considering the operation characteristics of load and storage resources i the source network under multiple time scales to strengthen the operational efficiency and cost-effectiveness of the power grid. The key contributions of this research include:

(1) Combined with the characteristics of an interactive power grid, a highly interactive active distribution network control architecture is proposed, a day-ahead scheduling model of a flexible load participation power system is constructed, and the optimal control process is obtained.

(2) A genetic algorithm (GA) is proposed to optimize the target, which greatly simplifies the complexity of the solution as well as avoids the problem of falling into the local optimal solution.

(3) Establish more accurate models for different types of loads to improve the solution accuracy.

## 2 Active Distribution Network Control Process Considering Flexible Load Interaction

### 2.1 Optimal Control Operation Architecture of Active Distribution Network

Modern distribution systems can be regarded as highly integrated cyber-physical systems with diverse structures. They adopt a control and management mode that combines centralized and distributed autonomous control via energy management systems at different levels. The control architecture of the active distribution network, which considers flexible load interaction, is shown in Fig. 1, adopting a centralized control approach. Once the distribution network control center receives dispatching commands from the platform, it communicates information through the dedicated digital channels of the backbone layer and the 5G network of the access layer and sends these commands to the terminal layer. The terminal layer reports the unit operation status to the control center using information and communication technologies, enabling two-way information interaction. Dispatchers plan and dispatch to optimize the economic operation of the system.

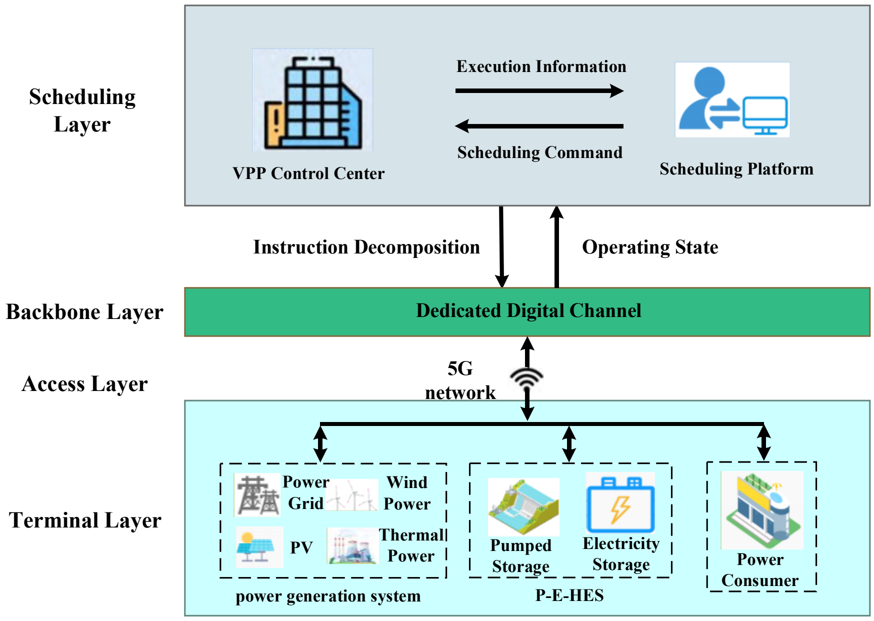


Fig. 1. Optimal control operation architecture of active distribution network

## 2.2 Multi-time Scale Coordination Optimization Scheduling Process

The introduction of multi-time scale collaborative planning in the distribution network involving multi-energy cooperative optimal dispatching can optimize the planning objectives. The multi-time scale coordinated optimization scheduling process is shown in Fig. 2.

The multi-energy cooperative optimization control adopts the multi-time scale sequential cooperative optimization scheduling mechanism. The whole life cycle cost of all kinds of equipment in the distribution network is calculated on a long-time scale, which provides macro guidance for the long-term development of the distribution network in county power grids. Enter the short time scale optimization scheduling stage and use advanced state estimation technology and intelligent algorithms to optimize and adjust the output of distributed energy. The real-time control link monitors the operation status of the distribution network and takes protective measures to guarantee that no faults occur during operation.

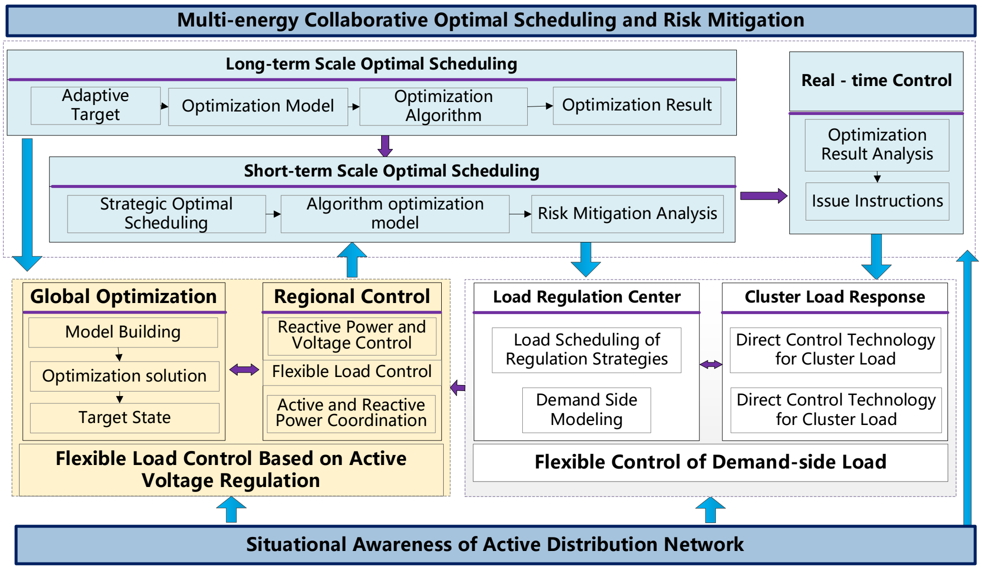


Fig. 2. Multi-time scale coordination optimization scheduling process

## 3 Flexible Resource Model

### 3.1 Distributed Power Supply Model

The amount of power grid generation is closely related to the situation of wind power generation, and its generation expression is:

$$0 \le g_{WPP,t} \le g_{WPP,t}^{f} \tag{1}$$

Where: $g_{WPP,t}$ and $g_{WPP,t}^{f}$ represents the scheduled and real-time forecasted wind power generation. The actual generation is:

$$g_{WPP,t}^{re} = g_{WPP,t}^{f} + \Delta g_{WPP,t}^{f} \tag{2}$$

Where: $g_{WPP,t}^{re}$ and $\Delta g_{WPP,t}^{f}$ are the value and error of the power generated by wind power generation. These prediction errors follow a normal distribution with parameters (0, $\sigma_t^W$), it can be measured through controlled - variable experiments that $\sigma_t^W$ is calculated through the following methodology:

$$\sigma_t^W = \frac{1}{5} g_{WPP,t}^{f} + \frac{1}{50} W_{WPP} \tag{3}$$

Where: $W_{WPP}$ is the whole capacity.

### 3.2 Controllable Load Model

According to the different ways of interacting with the power grid, the controllable load is subdivided into two types: incentive-based load curtailment (IBLC) and load shifting (LS).

IBLC load is equivalent to a "negative generator set", and the mathematical model established by IBLC is also corresponding to the model of the generator group. The load reduction of IBLC can be expressed as:

$$\begin{cases} P_{d,t}^{lc} = Q_{d0}^{lc} u_{d,t}^{lc} + \sum_{m=1}^{M} q_{d,m,t}^{lc} \\ 0 \le q_{d,m,t}^{lc} \le \bar{Q}_{d,m,t}^{lc} \end{cases} \tag{4}$$

Where, $P_{d,t}^{lc}$ denotes the load reduction of user d in period t; $Q_{d0}^{lc}$ represents the initial load reduction of the user, such as the minimum power reduction necessary to shut down or adjust the operation mode of a machine; $u_{d,t}^{lc}$ represents the user's cut mark, which is 0-1 variable; $q_{d,m,t}^{lc}$ means that the load can be reduced in subsequent sections. $\bar{Q}_{d,m,t}^{lc}$ represents the maximum load reduction of the user at a certain incentive compensation level.

When the IBLC user reduces the load, the original production plan or power consumption mode is interrupted, and the subsequent load demand of the user may be affected and continue to be reduced, or it could be that the minimum value is reached and can no longer be changed. The reduction time constraint of IBLC load is:

$$\begin{cases} \sum_{t'=t}^{t+LCT_d^{\min}-1} u_{d,t'}^{lc} \ge LCT_d^{\min} (u_{d,t}^{lc} - u_{d,t-1}^{lc}) \\ \sum_{t'=t}^{t+LCT^{\max}} u_{d,t'}^{lc} \le LCT_d^{\max} \end{cases} \tag{5}$$

Where, $LCT_d^{\min}$ and $LCT_d^{\max}$ represents the maximum/minimum reduction time for IBLC user d, similar to the minimum operating time constraint for thermoelectric units.

### 3.3 Degree of Environmental Pollution

During the operation of the system, polluting gases will be produced, causing a certain degree of damage to the environment. Therefore, the emission of polluting gases is the main environmental indicator for measuring the operation of the system. In order to promote environmental protection, it is stipulated that the power system needs to pay a certain amount of fine to the government to compensate for the pollution caused to the environment by its own operation. Since the polluting gases mainly come from cogeneration units and gas boilers, the environmental costs of the system operation are stipulated as follows:

$$\mathrm{C} = \sum_{t=1}^{T} \sum_{j=1}^{J} \omega_j \delta_j \left( \frac{P_{chp}(t)}{\eta_{chp}} + \frac{P_{GB}(t)}{\eta_{GB}} \right) \tag{6}$$

Where j is the pollutant gas type, including CO, $CO_2$, $SO_2$ and $NO_x$; $\delta_J$ is the emission coefffcient of pollutant gas j, kg/kW; $\omega_j$ is the environmental hazard degree of the pollutant gas $j$; $P_{chp}(t)$ and $P_{GB}(t)$ are the output power of CHP and GB, kW; $\eta_{chp}$ and $\eta_{GB}$ are the utilization efffciency of CHP and GB,%.

## 4. Dispatch Method of Load-Side Resources in Active Distribution Network

### 4.1 The Objective Function of the Adjustment

With the new energy and electric vehicles and other loads, the size and change of the peak-valley difference is more complex, peak regulation needs to be carried out in a wider range, the peak regulation method is more flexible, and the correlation between various peak regulation methods is stronger. How to coordinate effectively among all kinds of peak regulations directly determines security. Based on satisfying the operation, the interactive peaking cost of the source network is the most economical and comprehensive. The cost objective function of interactive peak load balancing of the source network is:

$$\min F = \sum_{\Delta T}(\sum_{i=1}^{N_G} C_i^g(t) + \sum_{i=1}^{N_R} C_i^r(t) + \sum_{i=1}^{N_L} C_i^l(t)) \tag{8}$$

Where, $N_G$ refers to the number of conventional peak-trimming units, including thermal power and hydropower units; $C_i^g(t)$ The cost of participating in peak regulation of unit $i$, such as start-up and shutdown; $N_R$ indicates the number of energy storage stations, including pumped storage and battery stations. $C_i^r(t)$ is participating in peaking costs for each energy storage power station; $N_L$ is the number of controllable load points, including load cutting and excitation load. $C_i^l(t)$ Participate in peak regulation costs for each controllable load. $T$ is to schedule a period.

#### 4.1.1 Thermal and Hydroelectric Power Units

Thermal power and hydropower used for peak regulation belong to conventional units, and conventional units have minimum technical output and maximum generation output constraints, that is:

$$P_{i,f,\min} \le P_{i,f}(t) \le P_{i,f,\max} \tag{9}$$

Where, $P_{i,f}(t)$ denotes the power of the unit, $P_{i,f,\min}$ , $P_{i,f,\max}$ represent the upper and lower operational limits, respectively.

This paper does not consider the economic cost of the unit output changes but considers the additional cost of the unit when the engine starts and stops running.

### 4.1.2 Energy Storage Power Station

Energy storage can also contribute to the operation of the system because the energy storage device can save the extra electricity through various means, so the power is not very needed on the side of the electricity, so the power generated by the grid exceeds the capacity that the user can consume, the energy storage device will start to run and save the extra power. This power is released to fill the gap when customers begin to need a lot of power and the grid cannot produce enough electricity for a short period of time to keep up with their needs. There are also constraints on the size of energy storage device output:

$$-P_{R,\max} \leq P_R(t) \leq P_{R,\max} \tag{10}$$

Where, $P_R(t)$ corresponds to the operational output of the energy storage facility, and $P_{R,\max}$ specifies its peak discharge capacity.

### 4.1.3 Controllable Load

The participants of load side peak regulation mainly include air conditioning, electric vehicles and other controllable loads. These loads account for a large proportion of the peak power consumption, which can shift the power consumption period, achieve peak shifting and valley filling, and relieve the peak load of the power grid. The constraint satisfies:

$$-P_{L,\max} \leq P_L(t) \leq P_{L,\max} \tag{11}$$

Where, $P_L(t)$ is the controllable load common rate and $P_{L,\max}$ is the maximum power of the controllable load.

### 4.2 Model Solving

This model represents an optimization problem that can be addressed using a genetic algorithm (GA). The GA is a stochastic search optimization algorithm inspired by natural biological evolution. It encodes potential solutions to a problem as chromosomes and employs operations such as population initialization, fitness evaluation, selection, crossover, and mutation to iteratively search for optimal solutions, allowing the population to evolve toward better solutions. The steps are as follows:

1. Population Initialization: Randomly generate an initial population of individuals, each representing a potential solution.
2. Fitness Evaluation: Assess the fitness of each individual based on an objective function to measure its quality.
3. Selection: Select individuals with higher fitness, using methods like roulette wheel selection, to participate in reproduction, ensuring they contribute more genetic material.

4. Crossover: Exchange genetic segments between selected individuals to generate new offspring, enhancing population diversity.
5. Mutation: Introduce small random changes to individual genes at a low probability to prevent the algorithm from converging to local optima.
6. Iteration: Repeat the above steps until a termination criterion is met, such as reaching a maximum number of iterations or achieving a stable fitness value.

The algorithm flow is shown in the Fig. 3.

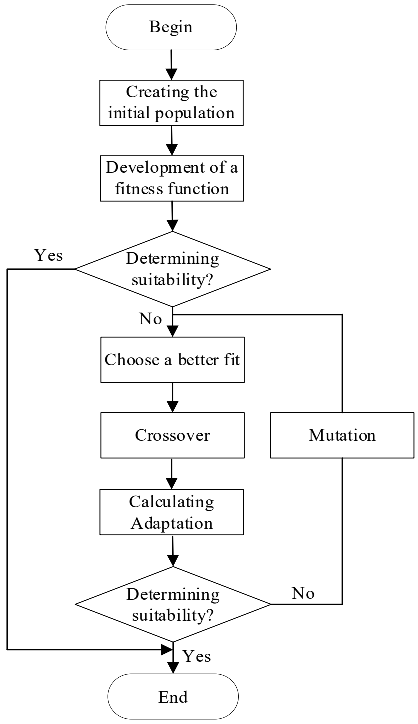


Fig. 3. The solving process based on GA

## 5. Case Study

Taking the comprehensive energy data of a regional power grid in 2024 as an example, the ratio of power supply capacity is shown in Table 1. First, the selection process for determining the best indeterminacy boundary is demonstrated through comparative cost analysis in Table 2. The predicted output of load and new energy is shown in Fig. 4. Empirical results reveal a cost trade-off pattern: as the uncertainty range expands, the robust scheduling model's constraints are progressively stricter, thereby amplifying energy production expenditures. Conversely, broader uncertainty parameters enhance the system's adaptability to fluctuating renewable energy outputs, effectively reducing operational risks associated with load cutting costs and the sum of wind/light curtailment. This cost-benefit relationship necessitates an equilibrium point where the composite expenditure reaches its minimum value, thereby establishing the most cost-effective uncertainty configuration.

*Table 1*

**Power capacity ratio of regional distribution network**

| Power supply type | Wind energy | Illumination | Thermal power | Gas | Hydro-power | Nuclear energy |
|---|---|---|---|---|---|---|
| Capacity/ (MW) | 976 | 200 | 2474 | 497.6 | 400 | 1300 |
| Percent/% | 15.1 | 3.1 | 38.4 | 7.7 | 6.2 | 20.2 |

*Table 2*

**Different uncertainties set various costs**

| Uncertain set ratio | 10% | 20% | 30% | 40% | 50% | 60% |
|---|---|---|---|---|---|---|
| Power generation + environmental cost (ten thousand euros) | 126.743 | 126.743 | 126.921 | 126.948 | 127.424 | 127.797 |
| Excision load (MWh) | 0.8065 | 0.7502 | 0.0921 | 0.0921 | 0.0642 | 0 |

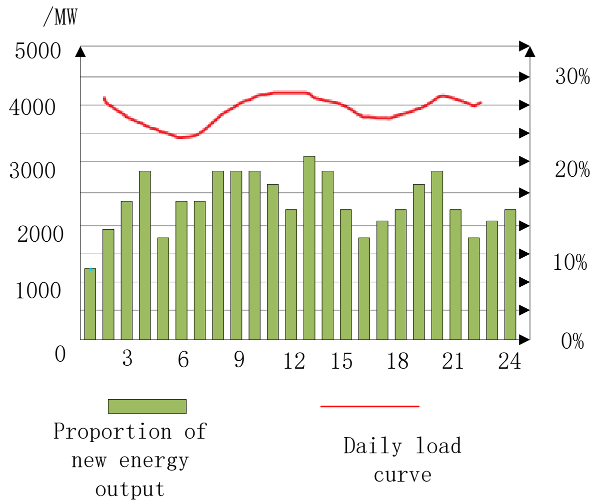


Fig. 4. Predicted output of load and new energy

Fig. 5 demonstrates that the minimal comprehensive expenditure occurs within the 20%-30% parameter range. With 1% as the error range, the binary search method is used to find the optimal uncertainty set of 20%. Table 3 illustrates the economic advantage of the cost-effectiveness achieved through optimized uncertainty configuration (20%) relative to alternative parameter selections. The analysis reveals the superior performance of this optimal solution.

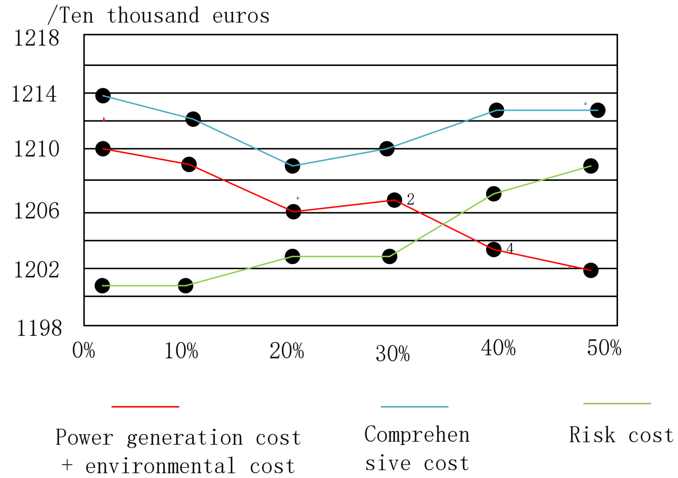


Fig. 5. Power capacity ratio of regional distribution network

*Table 3*

**Economic benefit of optimal uncertainty set**

| Uncertain set ratio | 10% | 20% | 30% | 40% | 50% |
|---|---|---|---|---|---|
| Comprehensive cost (ten thousand euros) | 1212.37 | 1209.55 | 1210.05 | 1212.76 | 1212.82 |
| Cost savings (ten thousand euros) | 1.63 | 4.45 | 3.95 | 1.24 | 1.18 |

Through cost analysis, it can be seen that the proposed method can effectively reduce overall cost expenditure and has significant economic advantages compared with traditional methods. Although this method increases risk costs to a certain extent, the substantial reduction in generator costs and environmental consumption costs indicates that the method enhances the utilization of renewable energy and avoids a large number of wind and solar curtailment phenomena. Overall, the advantages outweigh the disadvantages. At the same time, combined with the hierarchical optimization operation architecture of the distribution network proposed earlier, the system can be scheduled more accurately and timely, ensuring that the power grid can operate according to the expected operation mode.

## 6. Conclusion

Addressing the evolutionary trajectory toward diversified load types of distribution networks and the problem of system security scheduling, this paper proposes the optimal operation process and architecture of the distribution networks. This investigation employs multidisciplinary theoretical frameworks and validated case study simulations to derive critical findings:

(1) The intelligent centralized control system demonstrates the capacity for

comprehensive operational surveillance and conducts unified scheduling. On this basis, combined with multi-time scale cooperative regulation, the economy of system operation is improved.

(2) In this paper, a genetic algorithm is creatively introduced into the field of power system control for optimization. Compared with traditional algorithms, which are easy to fall into local optimality, the GA demonstrates distinguished global optimization capabilities, expediting the identification of the most economical state of system operation and reducing unnecessary operating costs.

(3) This paper creatively introduces the robust scheduling method into the integrated energy system and compares it with the traditional scheduling method to verify that the robust scheduling method can better coordinate the comprehensive utilization of various types of resources and promote the consumption and absorption of energy.

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