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Research on the Source-Load Interactive Scheduling Strategy for Modern Industrial Parks

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Research on the Source-Load Interactive Scheduling Strategy for Modern Industrial Parks

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Abstract. Aiming at the problems of diversified demand for electricity, high rate of load growth, limited distribution network corridor and single power supply mode in industrial parks, this paper explores a new scheduling strategy, studies a mechanism of source-load interactive scheduling for modern industrial parks, and puts forward three scheduling strategies, namely, optimal electricity price, friendly power grid and enhanced production. The strategy has been applied in a smart industrial park of Hunan Power Grid. The application results show that the method can effectively improve the power supply capacity of the modern industrial parks, reduce the total cost of electricity, and enhance the load rate of distribution transformers, and it also has high economic and practical value.

1. Introduction

On April 18, 2019, the National Energy Administration issued the *Energy Standardization Management Measures and the notice of implementation rules*, stipulating the requirements for the standardization of industrial energy consumption [1]. At present, modern industrial users are facing an important issue that how can they optimize energy consumption level and energy supply model. In this context, the power supply scheduling mode of traditional industrial parks is also rapidly falling behind, which cannot meet the capacity requirements of modern industrial parks [2-4].

In recent years, with the rapid development of information technology such as Internet of Things and artificial intelligence and its widespread use in production and life, it has become a research hotspot at home and abroad to apply new technology innovation scheduling mode and improve the energy utilization rate and new energy consumption level of industrial parks. Reference [5], an optimal scheduling model with minimum operating cost and minimum grid loss is established. The simulation results show that the proposed scheduling method can effectively reduce system operating costs and grid loss and improve new energy consumption level. Literature [6], based on the characteristics that the prediction error and the load prediction error decrease with time scale, a rolling scheduling model considering the change of prediction error is established. Literature [7] comprehensively considers power users and power supply enterprises, and establishes a multi-target variable-time optimal model to reduce electricity tariffs. An optimal scheduling model for wind power-based power systems considering user satisfaction and electricity price response was established in [8]. The model coordinated optimization control of load resources and power generation resources, reducing system operating costs and reducing the start-stop costs of the units. Reference [9], combined with fuzzy opportunity programming constraints and credibility theory, a fuzzy chance constrained scheduling model for dynamic economic scheduling is constructed.

The above literature studies only consider the dispatching model of power supply side or user side, not the optimal dispatching model with multi-agent participation. In order to further optimize, a dynamic coupling scheduling model of energy supply and industrial production is proposed in reference [10]. It is applied in battery factories to reduce the cost of energy consumption in industrial production. Literature [11] has carried out the research on the interaction mechanism between energy supply and multi-participant industrial parks, which has a certain effect on reducing peak load and valley filling and alleviating the shortage of power supply.

Based on the characteristics of modern industrial parks, such as large energy demand, regional concentration, obvious energy use plan, complementary time periods, and multi-energy complementary operation [12-14]. This paper studies the mechanism of “production-energy-ring” source-drain interaction for modern industrial parks, and proposes three target optimization strategies to improve the power supply capacity of modern industrial parks, reduce the cost of electricity for users, and increase the load rate of distribution transformers.

2. Optimal scheduling model

According to the current power supply problem and power demand in the industrial park, three scheduling models are established, there are the electricity price optimal model, the grid friendly model and the production strengthening model.

2.1. Electricity price optimal model

The electricity price optimization model aims at the lowest electricity tariff for industrial park users. The total electricity cost of the park is the sum of the electricity consumption of all electricity loads in the park and the electricity tariff. The design electricity tariff model expression as follows:

$$V=\sum_{m=1}^{5}\sum_{n=1}^{N}V_{mn} \tag{1}$$

$$V_{mn}=a_nW_{mn} \tag{2}$$

Where, V_{mn} is the electricity charge generated by the load of m in the n period, an is the n-period rate, W_{mn} is the amount of electricity generated by the load of m in the n-time period.

Under the electricity price optimization strategy, the requirement of $V=\sum_{m=1}^{5}\sum_{n=1}^{N}V_{mn}$ are the lowest in various W_{mn} combination need to be satisfied, and the following constraints are met:

$$\begin{cases}\sum_{m-1}^{5}W_{mn}\le W_{\max}(T_n)\\ W_{mn}=f_m(P_{mn})\\ \sum_{n-1}^{D}P_{mn}=\overline{P_m}\\ W_{mn}\le \max(W_m)\end{cases}$$

2.2. The grid friendly model

Grid-friendly means that the utility load is as balanced as possible. Total load = mains load + wind load + photovoltaic load + energy storage system load, therefore, mains load = total load - wind load - photovoltaic load - energy storage load. Among them, the wind power load and the photovoltaic load can be predicted and obtained according to the weather conditions, therefore, total load and can be roughly estimated according to the production demand, and the energy storage system can be adjusted within an appropriate range to design the load model as follow:

$$W_{\text{mains}}=W_{\text{total}}-W_{\text{wind}}-W_{photovoltaic}-W_{\text{storage}} \tag{3}$$

$$W_{\mathrm{mains}T} = \sum_{\mathrm{i}=1}^{5} W_{\mathrm{mains}iT} \tag{4}$$

$$\overline{W_{\mathrm{mains}}} = \frac{\sum_{T=1}^{n} W_{\mathrm{mains}T}}{n} \tag{5}$$

$$s = \sqrt{\frac{\sum_{T=1}^{n}\left(W_{\mathrm{mains}T} - \overline{W_{\mathrm{mains}}}\right)^2}{n-1}} \tag{6}$$

Where $W_{\mathrm{mains}iT}$ is electricity load of mains load in a certain production scenario for T period, $W_{\mathrm{mains}T}$ is the total demand of the mains load in a certain period of time, and s is the standard deviation of the mains load curve of the park.

Under the grid-friendly strategy, the minimum standard deviation of the mains load curve is obtained, and the constraints are:

$$\begin{cases} W_{\mathrm{mains}} = W_{\mathrm{total}} - W_{\mathrm{wind}} - W_{photovoltaic} - W_{\mathrm{storage}} \\ \sum_{m=1}^{5} W_{\mathrm{total}mn} \le W_{\mathrm{total\,max}}(T_n) \\ W_{\mathrm{total}mn} = f_m(P_{\mathrm{total}mn}) \\ \mathrm{W_{wind}} = f_1(\mathrm{T}) \\ \mathrm{W_{photovoltaic}} = f_2(\mathrm{T}) \\ \mathrm{W_{storage}} = f_3(\mathrm{T}) \\ \sum_{n=1}^{D} P_{mn} = \overline{P}_m \\ W_{\mathrm{total}mn} \le \max(W_{\mathrm{total}m}) \end{cases}$$

2.3. Production strengthening strategy model

Production strengthening strategy refers to the situation that production demand is more urgent, the demand of load is very large before a certain time node, and the demand decreases significantly after a certain node. So the load model is designed according to the output requirement as follows:

$$P_{\mathrm{Total}} = \sum_{m=1}^{5} \sum_{j=1}^{n} P_{mj} \tag{7}$$

$$P_T = \sum_{i=1}^{5} P_{iT} \tag{8}$$

$$\overline{P} = \frac{\sum_{T=1}^{n} P_T}{n} \tag{9}$$

$$s = \sqrt{\frac{\sum_{T=1}^{n}(P_T - \overline{P})^2}{n-1}} \tag{10}$$

$$W_{mj} = f_m(P_{mj}) \tag{11}$$

Under the production-strengthening strategy, the standard deviation is required to be the largest and meet the following constraints:

$$\begin{cases} P_1 \geq P_2 \geq \cdots \geq P_n \\ W_{mn} = f_m(P_{mn}) \\ \sum_{m=1}^{5} W_{mn} \leq W_{\max}(T_n) \\ \sum_{n=1}^{D} P_{mn} = \overline{P}_m \\ W_{mn} \leq \max(W_m) \end{cases}$$

3. Multi-objective optimization model and its solving algorithm

3.1. Multi-objective optimization model

Multi-objective optimization problem requires that each objective be optimized as simultaneously as possible in the restricted area. *A* multi-objective optimization problem with m minimum objective variables, *p+q c*onstraints and *D* decision variables can be described as follows:

$$\begin{aligned} & minF(x) = (f_1(x), f_2(x), \cdots, f_m(x))^T \\ & s.t. \quad g_i(x) \leq 0, i = 1,2,\cdots,p \\ & \qquad h_j(x) = 0, j = 1,2,\cdots,q \\ & x = [x_1, x_2, \cdots, x_d, \cdots, x_D,] \\ & x_{d\min} \leq x_d \leq x_{d\max}, d = 1,2,\cdots,D \end{aligned} \tag{12}$$

Where, *F (x)* defines m mapping functions from decision space to target space. *X* is a D-dimensional decision variable. $g_i \leq 0(i = 1,2,\cdots,p)$ and $h_j(x) = 0(j = 1,2,\cdots,q)$ are constraints.

Multi-objective optimization problem is a set of optimal solutions. The elements in the set are called Pareto optimal solutions.

3.2. Multi-objective optimization model

Particle swarm optimization (PSO) algorithm is a bionic algorithm [15] proposed by Kennedy and Eberhart inspired by the law of bird foraging activities. Multi-objective particle swarm optimization (MOPSO) combines Pareto sorting mechanism to find the historical optimal solution of particles by using the dominant relationship between particles. MOPSO uses efficient cluster parallel search to optimize the inferior solution, and can adjust the search strategy from time to time to accelerate the search speed, so the algorithm has better robustness and global convergence.

For particle swarm optimization of size N, the algorithms of particle position vector x_i, particle *i* and velocity vector v_i are separately expressed as follows:

$$x_i = (x_{i,1}, x_{i,2}, \cdots, x_{i,D})^T \in R^D \tag{13}$$

$$v_i = (v_{i,1}, v_{i,2}, \cdots, x_{i,D})^T \in R^D, i = 1,2,\cdots,N \tag{14}$$

D refers to the number of decision variables. In the evolution process, the particle position and velocity update mode are shown as follows:

$$v_{id}^{k+1} = \omega \cdot v_{id}^k + c_1 \cdot r_1 \cdot (p_{id}^k - x_{id}^k) + c_2 \cdot r_2 \cdot (p_{gd}^k - x_{id}^k) \tag{15}$$

$$x_{id}^{(k+1)} = x_{id}^{(k)} + v_{id}^{(k+1)} \tag{16}$$

Where, *K* refers to the number of evolutions; $\omega \geq 0$ refers to the inertia weight; *r1* and *r2* refer to the random numbers between (0, 1); *c1, c2* $\geq$ 0 refers to the acceleration coefficient; $p_{gd}^{(k)}$ refers to the d-dimensional component of the optimal position of the *k*-th evolution in the particle swarm, which is

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called G-best; $p_{id}^{(k)}$ refers to the d-dimensional component of the optimal position of the *i*-th particle in the *k*-th evolution, which is called P-best.

3.3. Solving steps

In the process of production, modern industrial park users need to reduce the cost of electricity as much as possible and meet the maximum production demand and power supply capacity. Therefore, power scheduling in modern industrial parks is a multi-objective optimization problem. This paper considers three optimization objectives, namely, optimal electricity price, enhanced production and friendly power grid. Constraints include power supply capacity, production plan and energy efficiency level, etc. The process of using the above multi-objective particle swarm algorithm to solve is as follows:

- Input objectives functions, i.e. Equations (1), (4) and (10), and start initialization;
- Initialize the particle swarm, initially assign the velocity and position of each particle, and initialize learning factor and number of iterations in Equation (15);
- Calculate the fitness value of particles, which is determined by three objective functions;
- Compare the fitness of particles, update the individual optimal position of particles (P-Best) and select the global optimal solution position of particles (G-best) according to the dominant relationship;
- Update Equations (14), (15) and (16) according to particle velocity and position;
- Determine whether the set maximum number of iterations is reached. If so, output the Pareto optimal solution set. Otherwise, return to Step (3) to continue the iteration;
- Select the minimum solution relative to positive and negative ideal points in the Pareto optimal solution set, that is, the optimal solution, which corresponds to the optimal scheduling strategy with the optimal electricity price, enhanced production and friendly power grid.

The specific solving process is as shown in Figure 1.

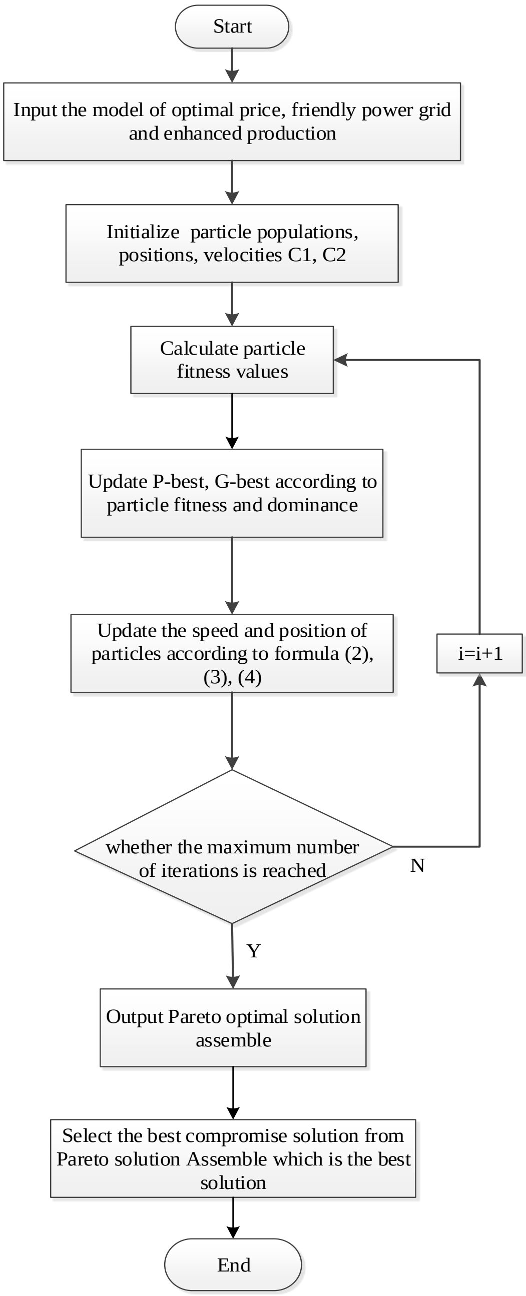

Figure 1 Flow Chart of the Solving Steps of Particle Swarm Algorithm

4. System Design

The system is designed according to the three-layer architecture, which is composed of global optimization layer, regional control layer and local control layer. The global optimization layer belongs to the decision-making center of the scheduling strategy for power supply and consumption in the parks, which collects the operation data of the entire network through the coordination of other layers. It is used to optimize the overall power consumption of the industrial parks to achieve optimal control strategy with optimal electricity price, friendly power grid and enhanced production. The regional control layer is centered on the coordinated controller, which is mainly responsible for regional power and load coordination on a short time scale. Based on the optimization objectives and reference information given by the global operational decision, it controls the energy storage system and the power load within the scope, achieves internal stability within its own region and reduces the interaction between different regions. The local control layer implements the strategy of global optimization layer according to the optimization control objectives given by the global optimization layer, controls and manages the power supply equipment and energy storage system of the parks, and achieves the application of three scheduling strategies (i.e. optimal electricity price, friendly power grid and enhanced production) on the side of distribution network. The structure of the control system is shown in Figure 2.

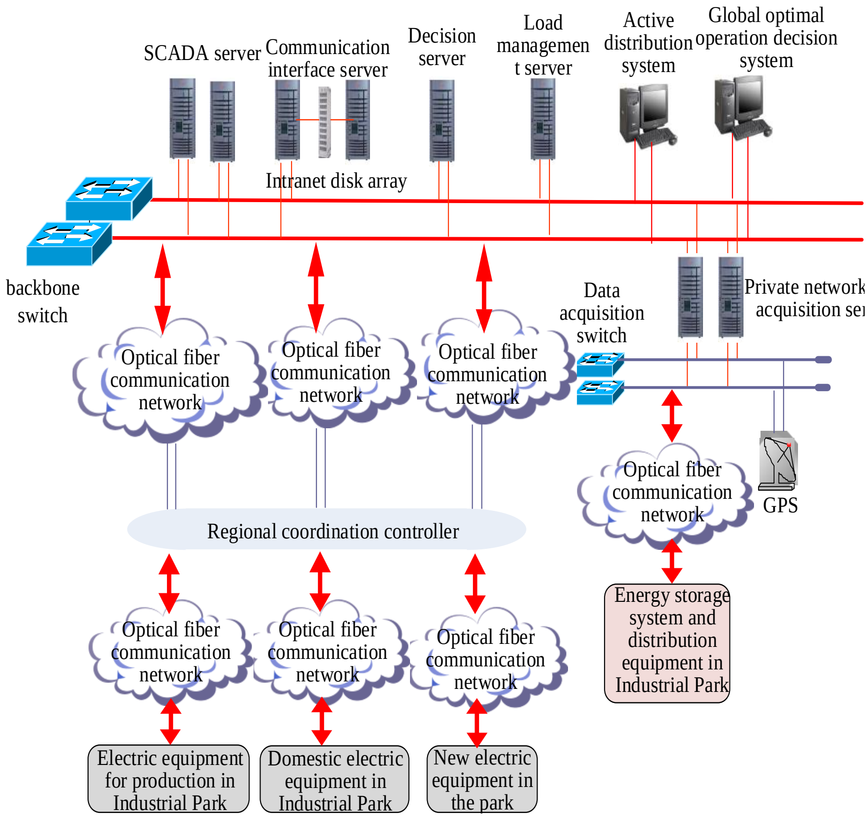

Figure 2 Diagram of Park Power Supply System Structure Based on Cyber-Physical System

5. Practical application effect

The source-load interactive scheduling strategy designed in this paper for modern industrial parks has been applied in a provincial smart park in Hunan. Through the established cyber-physical system, it collects and analyzes the electric equipment in the parks, and obtains the load-charge curves under three different power supply scheduling strategies, as shown in Figures 3, 4, and 5.

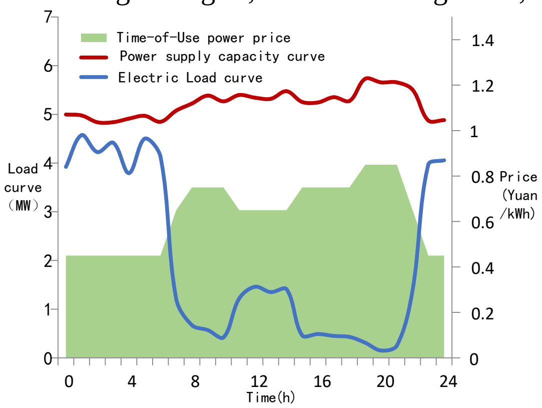

Figure 3 Load Charge under the Strategy of Optimal Electricity Price

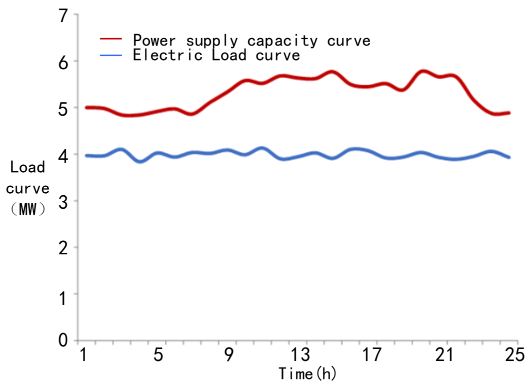

Figure 4 Load Curve under the Strategy of Friendly Power Grid

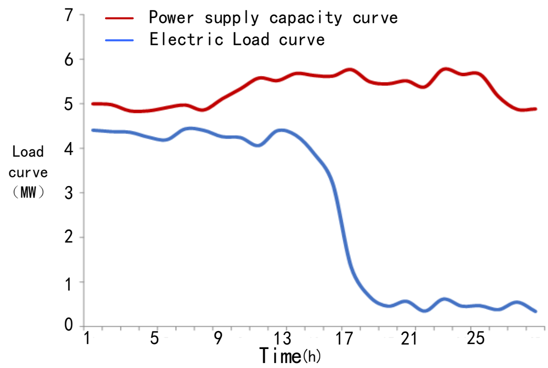

Figure 5 Load Curve under the Strategy of Enhanced

It can be seen from Figure 3 that under the strategy of optimal electricity price, the power load of the industrial parks is low under the condition of high electricity tariff, and the overall electricity cost for the park is reduced, which saves the electricity cost of park users. As shown in Figure 4, based on the goal of the lowest load volatility, the load fluctuation is reduced under the strategy of friendly power grid. As can be seen from Figure 5, under the strategy of enhanced production, the maximum production demand of users is satisfied and the power load of a certain node is greatly reduced in a short time, thus safeguarding the capacity of industrial production.

6. Conclusion

This paper designs a source-load interactive scheduling cyber-physical system for modern industrial parks based on cyber-physical fusion. It optimizes the scheduling mode from the aspects of optimal electricity price, lowest load fluctuation and production capacity, and proposes three strategies for source-load interactive scheduling. It has been proved by practice that the scheduling strategy can make the most efficient use of the power supply equipment, improve the load ratio of the power distribution equipment in the parks, increase effectively the production value of industrial park users, and optimize the energy structure. It has extremely high reference value and certain economic benefits to solve the problems of insufficient power supply and diversified power demand in modern industrial parks, and can be popularized and applied in advanced modern industrial parks in China.

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