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Key Problems of Source-Load Interaction in New Energy Power System Based on Multi-Objective Optimization

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Abstract: In the face of the current global shortage of fossil energy, the greenhouse effect seriously affects the development of the world economy and people's health, countries are actively seeking new energy(NE) to replace fossil energy, in order to achieve sustainable economic development and curb the continuous warming of the global climate, which will dominate the future development. At the same time, the breakthrough of modern technology in comprehensive energy technology makes the urban power grid gradually change to electricity-based, and includes water, heat, gas and other multi-energy supply forms. The increase in the installed scale of renewable energy(RE) has brought many problems to the operation and scheduling of the power system(PS). The NEPS(NEPS) actively and fully accepts RE, and its power supply side contains a large number of intermittent and random fluctuations of RE power. The existing optimal dispatch strategies for PSs including RE that consider emissions do not fully consider source-load interaction(SLI), and ignore the deep peak regulation of units and the joint dispatch of user loads under the new situation. To this end, this paper analyzes the user-side characteristics of wind, solar and thermal power generation(PG) units through the multi-objective optimization(MOO) model of the cost of the NEPS, and simulates five dispatching scenarios on the source-load interactive platform. The PS is optimally dispatched to reduce the economic cost of the unit.

1. Introduction

The operation of the PS should follow the constraints of the physical characteristics of the power grid itself, the constraints of the market economy and the constraints of the environment. Compared with the traditional power grid, the constraints faced by the NEPS have been upgraded. The volatility and intermittency of NE PG and the emergence of massive active load nodes on the demand side increase the physical characteristics of the power grid. The demand side participates in electricity market transactions and the impact of PG costs caused by carbon emissions trading, which changes economic characteristics and reduces EC. Emissions make environmental constraints more demanding than ever before [1]. Therefore, the SLI of the NEPS must ensure the safe, economical and environmentally friendly run of the system.

At present, research on the key issues of SLI in NE systems has achieved good results. For example, some scholars have introduced multi-agent technology to establish a demand-response multi-agent structure for distributed and decentralized decision-making, improving decision-making efficiency and coordination of resources within the region. Source-load coordination optimization scheduling is usually based on the analysis of the distribution law of power output and load demand, and a balance between RE consumption and the overall operating cost of the system can be achieved in order to achieve the purpose of SLI, coordination and efficiency [2]. Due to the introduction of the market mechanism, the environmental constraints of power production are directly transformed into economic constraints, and the marginal benefit of carbon ER is clearer, which can promote grid dispatching and PG enterprises to consciously save energy and reduce emissions [3]. The role of the energy interactive demand-side resources of the NEPS in energy conservation(EC) and emission reduction scheduling is mainly to provide zero-carbon PG resources. Due to the rising price of carbon emissions, the transaction price of the electricity market is too high [4]. It can be seen that the research on SLI basically focuses on reducing carbon emissions through the combination of NE and PSs, which has always been the current and future research direction.

This paper first analyzes the changes of the NEPS compared with the traditional PS, then proposes a SLI cost scheduling model based on MOO, and then designs a SLI platform, and conducts simulation scheduling experiments through this platform to analyze new Cost-optimized scheduling results for multiple generator sets of an energy PS.

2. Related Algorithms

2.1 The Fundamental Change Load Scheduling Problem of NEPS

(1) The dispatch mode of the NEPS needs to realize the integrated coordination of PG and power consumption. The traditional dispatching mode mainly considers the dispatching of the PG side, and adjusts the output of the generator set to meet the electricity demand; and one of the most important features of the smart grid is the interaction between the user and the power grid. At this time, the load is active and changing during the system operation. Scheduling objects need to take into account both the generator-side units and the demand-side resources [5-6].

(2) The optimization goal not only needs to consider the economy, but also the benefit of energy saving and ER. The driving force for the development of NEPSs comes from EC and ER. However, because the economic attributes of PG fuels and the natural emission attributes are not unified, economy and EC and ER are a pair of contradictions [7-8]. In addition, the characteristics of NE PG determine that NE PG must be attached to conventional energy units, and the substitution benefit comes at the expense of the PG efficiency of conventional units, and the resource value is difficult to accurately measure [9].

2.2 Cost Analysis of Source-Load Interactive Scheduling Based on MOO

The access of large-scale wind power(WP) and photovoltaic PG requires the adjustment of conventional generator sets to promote their consumption. From the perspective of the entire supply side, it is achieved through the coordinated output between power sources [10]. At present, there are also many achievements specializing in the joint optimal dispatch of WP-thermal to solve the problem of economic wind curtailment. UHV realizes the centralized development of WP bases and the LC(LC), high-efficiency, high-efficiency bundling and safe delivery of wind/light/thermal power, as well as the proposal and popularization of the concept of virtual power plants [11].

The total cost of the coordinated output of the power supply should be the sum of the operating costs of all power supplies C_S , and the calculation method is as follows:

$$C_S(T) = C1(T) + C2(T) + C3(T) + C4(T) \quad (1)$$

Among them, C1, C2, C3, and C4 are the operation and maintenance costs, depreciation costs, fuel costs of TPUs, and conventional generator set ACs of all power sources in the research period T, respectively. Among them, the operation and maintenance cost of the power supply includes the production and operation of the unit, and the technical transformation of eliminating deficiencies. The calculation method needs to consider the operating hours of the unit, and the cost is the sum of the operation and maintenance costs of all power sources. The depreciation cost of the power source is related to its initial investment cost and depreciation coefficient [12].

$$\begin{cases} C2 = \sum C_i \times f_i \\ f_i = \dfrac{r_i(1+r_i)^{b_i}}{(1+r_i)^{b_i}-1} \\ i \in \{WT, PV, TM, HY\} \end{cases} \quad (2)$$

In the formula, WT, PV, TM, and HY are the initial investment costs of WP, photovoltaic, thermal power, and hydropower units, respectively, f_i is the corresponding depreciation coefficient, r_i is the depreciation rate of unit type i, and b_i is the project service life of unit type i.

3. Source-Load Interactive Platform

My country's NEPS has the characteristics of wide distribution of addresses and locations, high order of magnitude of transmission energy, high-speed and reliable communication scheduling instructions, uninterrupted real-time balance, and instantaneous spread of major faults. These characteristics determine that NEPS data is typical big data [13]. For example, with the LC application of RE PG units, distributed power sources and smart power equipment, hundreds of millions of terminal equipment power consumption data, wind speed, light intensity, temperature and other meteorological monitoring data in different regions and WP forecasting The large amount of historical data required has put forward higher requirements for automatic control of PS, cooperative interaction between source and load, and online analysis and decision-making [14-15]. Therefore, the SLI platform must be built on the basis of big data technology. As an important part of power big data, it can obtain knowledge and information from massive data, optimize power production and distribution, and promote the reform of the power industry [16]. The architecture design of the source-load interactive platform is shown in Figure 1.

The Source-Load interactive platform is mainly divided into five levels: data source, data collection, data storage and processing, auxiliary decision-making and display.

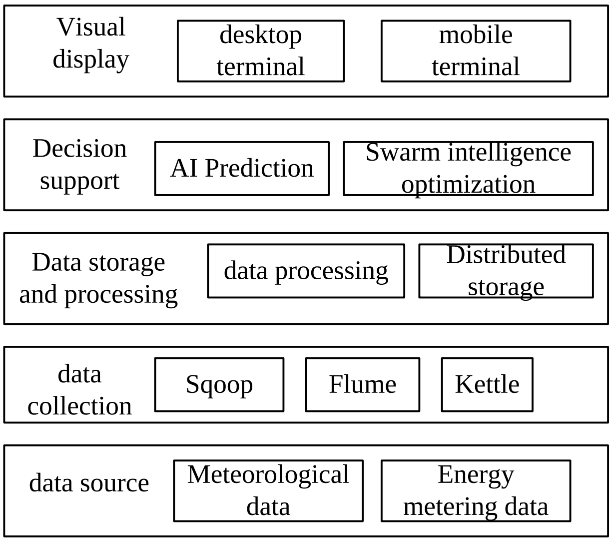

Figure 1. Source-Load Interactive Platform

The data source refers to the data source required for SLI, which is generally a relatively independent application system database, including economic data in the MIS system, meteorological data, real-time unit operation data in the SCADA system, and wind-solar power prediction data [17] .

Data collection refers to the organic concentration of data from different application systems and different formats on the logical or storage medium on the premise of keeping the original application system unchanged, including data communication and transformation (Sqoop), and the collection of massive logs. (Flume), file data processing (Kettle), etc.

The purpose of data storage and processing is to realize the integration and sharing of data, and to solve the problems of data redundancy and information islands among various systems within the power enterprise.

Auxiliary decision-making is the process of mining the potential value of big data and forming decision-making alternatives. By analyzing and calculating the content of the data, higher-level decision-making is realized based on data-driven, artificial intelligence, data mining and other technologies, such as multi-objective planning, cost allocation mechanism [18].

Visual display is mainly to display the conclusions obtained by assisting decision-making in a way that is convenient for users to understand, which includes the display of LC, high-dimensional, multi-source, and real-time changing information in the time and space dimensions. In this way, managers can more intuitively and accurately understand the meaning expressed by the conclusion in the process of SLI, and understand the operation state of the PS [19].

4. Example Simulation and Analysis

4.1 Different Scheduling Scenario Settings

The following 5 scenarios are designed to analyze the impact of energy storage(ES) system, demand response(DR), and carbon processing cost(CPC) on the consumption of wind-solar hydroPG. The scheduling scenarios can be carried out on the SLI platform.

Scenes A: This scene includes wind, light, and thermal PG units, regardless of battery ES power stations(PS), user-side DR, and CPCs.

Scenes B: Battery ES scene, this scene introduces battery ES power station based on Scenes A.

Scenes C: The SLI scene. Based on Scenes A, this scene introduces a day-ahead electricity price type virtual response unit and an intraday incentive type virtual response unit.

Scenes D: Low-carbon scenarios, which introduce CPCs based on Scenes A.

Scenes E: Comprehensive scene, which simultaneously introduces battery ES PS, user-side DR, and CPCs.

4.2 Basic Data

Taking a NEPS in a certain region as an example, the system includes thermal power plants with an installed capacity of 1200MW, wind turbines with a capacity of 200MW and photovoltaic power plants with a capacity of 400MW. According this model predict the energy consumption of wind turbines and photovoltaic PG, and the prediction curve is shown in Figure 2.

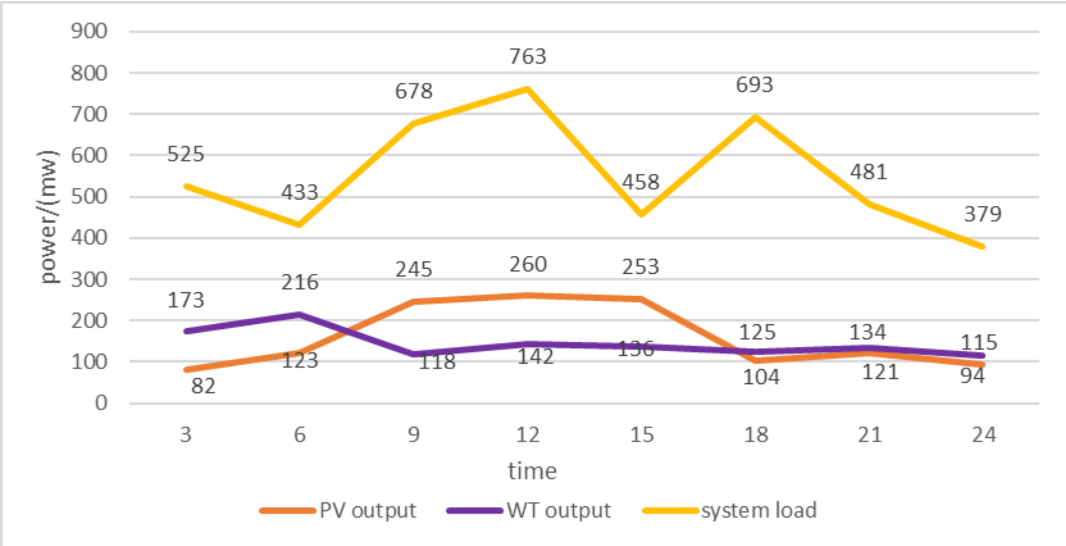

Figure 2. Forecast curve

4.3 MOO Cost Analysis Results

Table 1. Optimized scheduling costs for different scenarios

	Scenes A	Scenes B	Scenes C	Scenes D	Scenes E
TPU cost	45365	42518	25346	38693	22538
ES power station cost	none	2364	none	none	2547
DR scheduling cost	none	none	21742	none	22085
Unit dispatch cost	10437	9458	2860	9214	5255
Limit PG costs	6739	6107	1254	8475	3319
TSC	62541	60447	51202	56382	55744

Table 1 shows the optimal dispatching cost for each dispatching scenario. In the basic scenario

(Scenes A), there is no ES PS and DR participation, the thermal power unit(TPU) is in a state of deep peak regulation(PR), and the TPU cost and average adjustment cost(AC) are relatively high, respectively 453.65 million Yuan and 104.37 million yuan. Scenes B includes a battery ES system, which relieves the PR pressure of TPUs, reduces the output cost of TPUs accordingly, and reduces the average AC of the intraday stage. In Scenes C, the user-side DR virtual unit participates in scheduling, which improves the uncertainty of the system load in two stages, one day before and one day, and effectively avoids the impact of load fluctuations on system operation. The CPC is introduced in Scenes D. In order to realize low-carbon dispatching, the output of TPUs is limited, and the amount of abandoned wind and light is reduced, and the total system cost(TSC) is reduced by 61.59 million yuan compared with the basic scene. This shows that in the integrated dispatching process of SLI, considering the system The overall operating cost, actively abandoning the use of some RE. Scenes E integrates various factors. In the simulation results, the unit AC is reduced to 52.55 million yuan, and the TSC is reduced by 10.87% compared with the basic scene.

Table 2. System Load (MW) Before and After DR

	3	6	9	12	15	18	21	24
System load before DR	441	537	624	765	563	832	610	408
System load after DR	483	515	598	684	579	766	625	433

Table 2 shows the power load of the system before and after users participate in DR. Load shifting reduces the energy load , while the cost of electricity increases significantly. Load fluctuations, the power supply pressure on the power supply side during peak hours is alleviated, and electricity interest rates are significantly improved during valley hours. Combining with Table 1, it can be seen that the user's participation in DR effectively reduces the AC of the unit and the TSC.

Analyze the influence mechanism of system optimization results under five scenarios, and the average AC and TSC under each scenario are obtained through optimization, as shown in Figure 3.

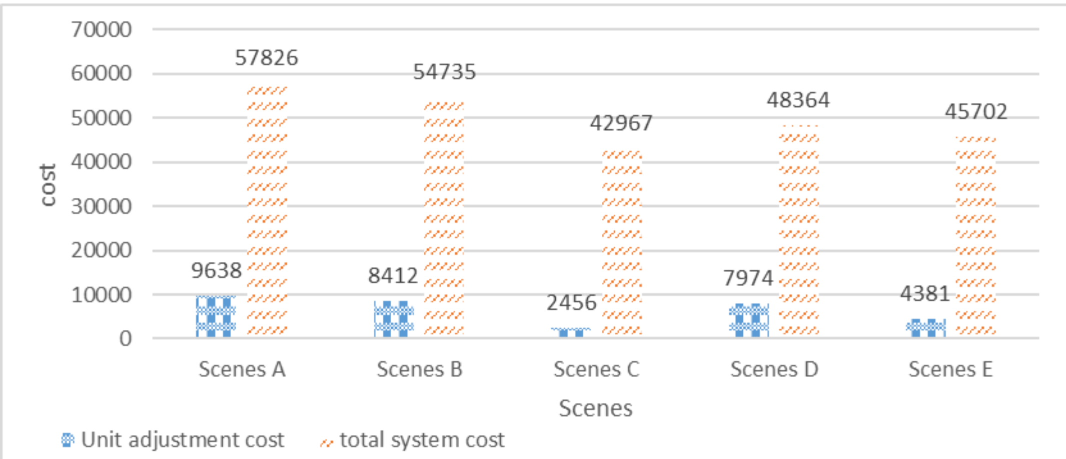

Figure 3. System optimization scheduling under different degrees of certainty

Comparing Table 1 and Figure 3, comparing the basic scenario and the comprehensive scenario before and after the prediction accuracy is reduced, the multi-energy coordinated two-stage optimal scheduling of DR has the smallest increase in the TSC, and the unit AC is relatively lower. Compared with the Scenes A, the Scenes E has less influence on the total operating cost of the load forecast error, which indicates that the internal SLI in the day-a-day and intra-day two-phase internal SLI is less affected. Adding it can improve the ability of the NEPS to deal with forecast errors and reduce the economic cost of the unit.

5. Conclusion

The proportion of RE in the power grid will be higher and higher, and the planning, construction and management of the PS will undergo changes. After LC RE is connected, the stability and economic problems of the PS are NE power. A major problem to be solved urgently in the system. In this regard, this paper studies the SLI problem of the NEPS, and establishes a MOO model for the economic cost of the generator set to optimize the cost scheduling. The experimental results prove that the addition of the SLI can reduce the economic cost of the generator set.

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