Research on Power System Joint Optimal Generation Scheduling Based on Improved Balance Optimizer

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This article presents a power system joint optimization generation regulation method based on the improved balance optimizer, which takes the five factors of power system network loss, voltage offset, generation cost, fuel cost, and comprehensive pollution emission as the objective function and takes the internal power balance of the system, each generator set, generation capacity, generation flow, and up and down climbing as the constraints. Fully considering the current energy-saving development objectives and the impact of economic dispatching, taking stable and safe operation as the core, the power generation dispatching model is established by improving the balance optimizer. The model realizes the maximum power generation with the lowest energy consumption parameters and transitions from the original power generation energy consumption of the power system to the best energy-saving power generation energy consumption so that the power value of the system reaches the target balance and completes efficient dispatching. Simulation experiments show that the proposed method can ensure the most reasonable power load in both summer and winter. The average load in summer and winter is reduced from 254.78/mw to 205.36/mw, down about 19.39%, which can ensure the power generation stability of the power system. The average power generation cost after dispatching is 129,920 $/h, which is significantly improved by comparing with 131,225 $/h before dispatching and can realize certain environmental benefits.

Keywords: balance optimizer, power system, objective function, energy consumption parameters, power generation cost

INTRODUCTION

At this stage, with the continuous development of the power era, the development of power technology is an important task that cannot be ignored by all countries at this stage. People's life, entertainment, and social production are inseparable from the support of power. However, with the increasing power consumption of users and the large-scale high load (Le et al., 2021) power consumption of various large enterprises, in order to speed up the pace of production, system failures occur frequently and the internal power distribution is uneven. The long-term uneven distribution will not only lead to short circuit (Toyoda and Wu, 2019), power climbing, and insufficient or excessive power generation but will also lead to unstable operation of the power system, increased cost, and poor power generation efficiency (Wu et al., 2020). Based on this, it is necessary to make reasonable arrangement and dispatching planning. Effective generation dispatching can not only

make the operation of the power system more stable without fault impact but also recover the highest benefit return with the lowest generation cost.

This literature (Zhang et al., 2022) mainly aims at the mixed phenomenon of AC and DC in the power system. The power generation problem of the system is quasi-transformed into the optimal power flow calculation problem. Taking four groups of phenomena such as network loss, power generation cost, pollutant emission, and voltage offset as the objective function, the differential evolution method is used to solve the generation scheduling parameters of the four groups of objective functions. The literature (Li et al., 2021a) proposed a genetic algorithm based on the neural network. Compared with the traditional methods, the genetic algorithm can capture the key information affecting power generation faster so as to converge to higher quality reactive power optimization scheme better and faster. The document (Li et al., 2021b) proposes the generation scheduling optimization strategy of swarm intelligence algorithm, which divides the optimal generation scheduling into two stages: search and utilization. The search process generally introduces disturbance variables so that the whole optimization process can find the target value faster and achieve global and large-scale optimization. Hu et al., (2020) propose an optimal generation scheduling algorithm with key parameter constraints. By setting different scheduling parameters for different generation values, it makes detailed optimization in the process of continuous updating among them. Shan et al., (2020) adopt a cross-platform generation scheduling algorithm, set models that can describe different nodes in the power system, and establish a joint scheduling threshold for scheduling. Yan et al., (2016) calculates the power value with linear change in the power system, sets the standard threshold, finds the power points that do not conform to the linear change, and implements generation dispatching.

On this basis, considering the abovementioned shortcomings and adverse effects, this study proposes a power system joint optimal generation scheduling method based on the improved balance optimizer. Balance optimizer is a new intelligent algorithm. It adopts the power generation optimization strategy inspired by the balance physical phenomenon based on the control volume mass and has strong data optimization ability, fast calculation speed, and fast convergence speed. First, the objective function is established, and then the condition constraints are carried out. An improved balance optimizer method is used to build a joint optimal generation scheduling model. On the basis of the original balance optimizer, the power variation objective function considering the actual maximization of the power system is added, and the objective constraint function is used to further approximate the optimal dispatching value. The optimization strategy can better adapt to the actual power generation situation of the power system and shows relatively best optimization performance. After the completion of dispatching, the system generates electricity smoothly, reduces the cost and power consumption, and greatly improves the operation efficiency.

OBJECTIVE FUNCTION ESTABLISHMENT

The improved balance optimizer follows the principle of mass balance equation in physics and describes the whole process of mass entering, leaving, and generating in a control volume. When applied to the joint optimal generation scheduling of the power system, the power target can be regarded as a mass point, the process of this mass point can be described, and finally the most balanced power value can be output. The objective function described, based on the improved balance optimizer, is

1) Power system network loss, expressed as

$$\min f_1 = \sum_{i,j \in N} G_{ij}\left(U_i^2 + U_j^2 - 2U_iU_j \cos \theta_{ij}\right) \qquad (1)$$

In the formula, N represents the number of all nodes in the power system; G_{ij} represents node i and node j line conductance; U_i、 U_j represents the maximum voltage value of node i and j at the position of the node, respectively; θ_{ij} represents the maximum electrical damage that node i and node j can withstand.

2) Voltage offset

$$\min f_2 = \sum_{i \in N_B|U_B^i - 1.0|} \qquad (2)$$

In the formula, U_B^i represents the voltage value of the power load node i; N_B indicates the number of nodes.

3) Power generation cost, the average cost consumption of power generation fuel can be expressed as

$$\min f_3 = \sum_{i=1}^{N_G}\left[a_i + b_iP_G^i + c_i\left(P_G^i\right)^2\right]. \qquad (3)$$

In the formula, a_i represents the lowest cost coefficient of the power system; b_i represents the highest cost factor; N_G indicates the number of generator nodes; and P_G^i indicates the active power value of the second generator set. The penalty function (Li et al., 2016) is established to restrict the state variables of uneven output in the i power system, and the objective function to be optimized is expressed as

$$\min J = f_k + \eta_U \sum_{i \in N_B} \Delta U_i + \eta_Q \sum_{j \in N_G} \Delta Q_j, \qquad (4)$$

of which

$$\Delta U_i = \begin{cases} U_i - U_i^{\max}, U_i > U_i^{\max} \\ 0, U_i^{\min} < U_i < U_i^{\max} \\ U_i^{\min} - U_i, U_i < U_i^{\min} \end{cases}. \qquad (5)$$

$$\Delta Q_j = \begin{cases} Q_{G.j} - Q_{G.j}^{\max}, Q_{G.j} > Q_{G.j}^{\max} \\ 0, Q_{G.j}^{\min} < Q_{G.j} < Q_{G.j}^{\max} \\ Q_{G,j}^{\min} - Q_{G,j}, Q_{G.j} < Q_{G,j}^{\min} \end{cases}. \qquad (6)$$

In the formula, f_k represents the solution objective; η_U represents the penalty coefficient indicating reactive power output of the load node; η_Q indicates the penalty coefficient of generator reactive power output; ΔU_i represents the penalty variable representing load node; ΔQ_j represents the penalty variable of the generator.

4) Fuel costs. The power generation fuel characteristics of the power system can be expressed by the quadratic function (Long et al., 2018), and the system fuel cost is

$$\min F = \sum_{i=1}^{N_G} F_i(P_i). \tag{7}$$

In the formula, N_G indicates the number of generator sets in the system; P_i indicates the active output value of the generator; and $F_i(P_i)$ represents the energy consumption characteristics. Considering that the normal valve point effect will appear when the generator set is affected by other factors (Martinez Caama et al., 2017), the energy consumption characteristics of the generator are expressed as

$$F_i(P_i) = a_i + b_iP_i + c_iP_i^2 + \left|e_i\sin\left(f_i\left(P_{i\min} - P_i\right)\right)\right|. \tag{}$$

In the formula, a_i, b_i, and c_i all represent the rated cost coefficient of the power system generator; e_i, f_i indicates the valve point effect parameter; and $P_{i\min}$ indicates the output limit of generator active power.

5) Comprehensive emission of pollution (Souza et al., 2018a). The emission calculation formula is

$$E = \sum_{i=1}^{N_G}\left[10^{-2}\left(\alpha_i + \beta_iP_i + \gamma_iP_i^2\right) + \zeta_i\exp\left(\lambda_iP_i\right)\right]. \tag{8}$$

In the formula, α_i, β_i, γ_i, ζ_i, and λ_i all represent the pollution emission coefficient generated by power generation; E represents total emissions.

CONSTRAINT FUNCTION

The objective function and constraint conditions belong to a complementary variable relationship. In the whole power generation dispatching system, the objective function is not only the reference of the dispatching model but also the independent variable, and the constraint conditions are appropriate linear programming based on the objective function, which is also the dependent variable. The constraint model of the power system is given as follows.

Internal power balance constraints (Souza et al., 2018b) refer to the balance between power supply and load in the power system. The generation capacity of the power system is determined according to the predicted power system load, which is a part of power planning. Restricting it can help the power system to achieve smooth operation:

$$\sum_{i=1}^{N_t}P_{gi,t} + \sum_{j=1}^{N_h}P_{hj,t} = P_{D,t} + P_{L,t}. \tag{9}$$

In the formula, N_h indicates the number of generator sets in the power system; $P_{hj,t}$ represents the generation output constraint value of the t generator set in the time period; $P_{D,t}$ indicates the system load; and $P_{L,t}$ indicates the system network loss.

Output (Abdin et al., 2022) constraint of the fuel generator set. As an important part of the power system, the fuel generator set can help achieve accurate dispatching in the next step by adopting the targeted constraint strategies:

TABLE 1 | Load required in 24 h.

Period	1	2	3	4	5	6
Load/MW	1288	1623	1300	1389	1520	1679
Period	7	8	9	10	11	12
Load/MW	789	1450	1300	925	1600	1450
Period	13	14	15	16	17	18
Load/MW	1620	1300	1450	1360	1700	985
Period	19	20	21	22	23	24
Load/MW	1350	1254	1311	1786	1426	1654

$$P_{gi}^{\min} \le P_{gi,t} \le P_{gi}^{\max}. \tag{10}$$

In the formula, $P_{gi}^{\max}$ indicates the upper limit of the output of the fuel generator set.

Output constraint of the kerosene generator set:

$$P_{hj}^{\min} \le P_{hj,t} \le P_{hj}^{\max}. \tag{11}$$

In the formula, $P_{hj}^{\max}$ indicates the upper limit of the active output of the kerosene generator set and $P_{hj}^{\min}$ indicates the lower limit of the active output of kerosene generator set.

Generation capacity limitations. Including normal operation capacity, emergency reserve capacity, and maintenance reserve capacity and taking the maximum capacity that the power system can bear as the objective, the constraint function is established:

$$V_j^{\min} \le V_{j,t} \le V_j^{\max}. \tag{12}$$

In the formula, $V_{j,t}$ represents the rated generating capacity of the j generator set in the time period (Silva et al., 2021); $V_j^{\max}$ represents the maximum generating capacity; and $V_j^{\min}$ represents the minimum generating capacity.

The power generation flow is about (Ebramsyah et al., 2017) bundles. Generation flow is an important index to evaluate the superiority of power dispatching, and the constraint function is established according to the national flow standard:

$$Q_j^{\min} \le Q_{j,t} \le Q_j^{\max}. \tag{13}$$

In the formula, $Q_{j,t}$ represents the generation flow value of the j generator set in the time period; $Q_j^{\max}$ represents the maximum value of power generation flow; and $Q_j^{\min}$ represents the minimum value of power generation flow.

Generation Load Balancing Constraints

Table 1 shows the load required for power generation load balance, and the average value used as the load reference standard.

$$V_{j,t} = V_{j,t-1} + I_{j,t} - Q_{j,t} - S_{j,t} + \sum_{k=1}^{N}\left(Q_{h,t-\tau_{ij}} + S_{h,t-\tau_{ij}}\right). \tag{14}$$

In the formula, $I_{j,t}$ indicates the system charge and inflow power of the j generator set in the time period; $S_{j,t}$ represents the system charge and outflow of the j generator set in the time period; N_u indicates the inflow time; and τ_{ij} indicates the outflow time.

Generation constraints at the beginning and end of the power system. The power period is segmented to restrict the power generation at the beginning and end of the period:

$$\begin{cases} V_{j,0} = V_{j,bepin} \\ V_{j,T} = V_{j,ead} \end{cases}. \tag{15}$$

In the formula, $V_{j,bepin}$ indicates the initial electric capacity and $V_{j,ead}$ indicates the final capacitance.

The reactive power constraint of the generator set. It means that in an AC circuit with reactance, the electric field or magnetic field absorbs energy from the power supply in one part of a cycle and releases energy in the other part of the cycle. The average power in the whole cycle is zero. It is related to the problem of repeated energy exchange between the power system and power supply:

$$\begin{cases} P_{gi,t} - P_{gi,t-1} \leq R_{U,i} \\ P_{gi,t-1} - P_{gi,t} \leq R_{D,i} \end{cases}. \tag{16}$$

In the formula, $R_{U,i}$ represents the upper limit value of reactive power output of the generator set and $R_{D,i}$ indicates the lower limit of reactive power output of the generator set.

Climbing Event Constraints on Power Load

Due to the influence of external factors or human factors, the power system is prone to power load climbing events. Power load climbing (Meyendorf et al., 2017) refers to the phenomenon of large-scale increase or decrease of system power in a short time, which is easy to cause an imbalance of system active power, destroy the frequency stability, and even cause large-scale die-cutting load, which seriously threatens the safety and stability of power grid and economic operation. In this article, this kind of event is regarded as an accidental event for optimal generation scheduling for scheduling regulation, and the changes of power system voltage, fluctuation rate (Dong et al., 2020), and other parameters during power load climbing are solved. The prediction algorithm is used to predict the linear change of power in the next step, and reasonable scheduling is carried out according to the change value.

There is T_{s1} increasing trend at the second time point, so the load shedding strategy is adopted. When the downhill climbing event occurs in the power system, it will disrupt the original power generation plan and lead to insufficient reserve capacity, which will affect the effective implementation of the system dispatching plan. Therefore, by increasing the power load climbing power constraint, the standby capacity of the conventional units in the power system is always higher than the maximum amplitude of power fluctuation, and the climbing rate is always lower than the maximum rate of power fluctuation by using the same principle. In this way, the power value and climbing value are in a stable suppression state for a long time:

$$\sum_{i=i}^{N} U_{i,t} \geq \Delta P_d + \Delta P_{Lu}. \tag{17}$$

$$\sum_{i=i}^{N} D_{i,t} \geq \Delta P_u + \Delta P_{Ld}. \tag{18}$$

$$\sum_{i=i}^{N} U_{i,t}' \geq \Delta P_d + \Delta P_{Lu}. \tag{19}$$

$$U_{i,t}' = r_{i,u} \times t. \tag{20}$$

In the formula, ΔP_{Ld} represents the rise of the power system per unit step during the whole climbing process; ΔP_{Lu} indicates the amount of decline; ΔP_d represents the maximum rise amplitude per unit step; and ΔP_u indicates the maximum drop amplitude.

Climbing Event Constraint Under Power Load

The downward climbing and upward climbing performance of the power load are basically the same, both in a phased downward (Calzarossa et al., 2019) trend, and there is a downward trend at the second time point. The maximum climbing amplitude is set in the unit of rated step size of the power system (Prada, 2017) as ΔP. The starting time of power load climbing is T_{end} and end time is T_s. According to the abovementioned **Formula 18**, it is determined whether the rated power generation value meets the minimum demand when the system ascends. If so, the abovementioned process is used to restrict; if not, specific constraints shall be imposed according to the following conditions:
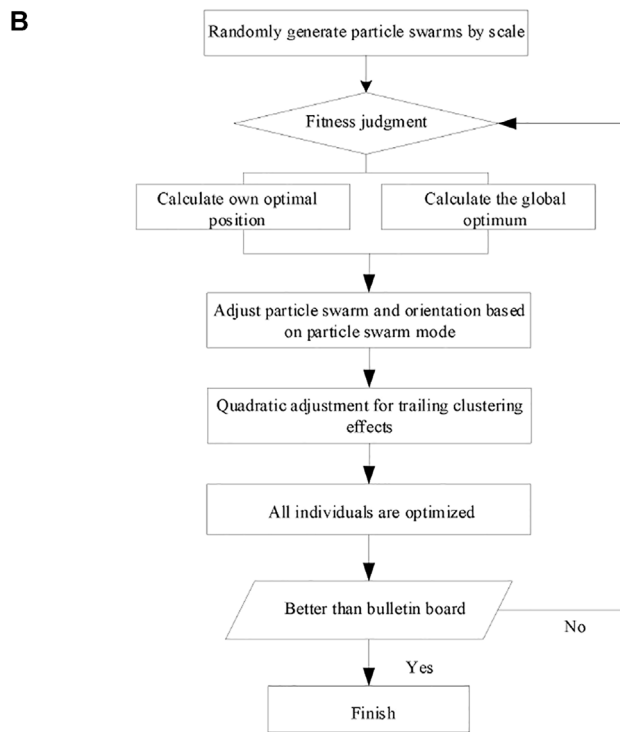
1) When the system goes downhill, a reasonable load shedding method shall be adopted before starting time T_s to shorten the power climbing time and increase the power correction time of the system.
2) When the system goes downhill, after the starting time T_s, according to the dispatching strategy proposed (Tian et al., 2016) previously, the output value of other units in the system can be increased by properly adjusting the output value so as to achieve operation balance and improve the overall adaptability of the system.

GENERATION SCHEDULING MODEL OF POWER SYSTEM

Based on the peak valley TOU price on the demand side, the energy-saving power generation dispatching on the generation side (Chao et al., 2016) is globally optimized. Through the analysis of the time price response of the user end, it can be seen that the market means will change the original system load distribution pattern. Through peak load regulation (Faghihi et al., 2016) and valley filling, the system load fluctuation level is reduced, the unit peak load regulation pressure is reduced, the utilization rate of the high-energy units is improved, and the coal consumption of the corresponding units is reduced. In view of this, an energy-saving generation scheduling optimization model based on the global (Kelley et al., 2018) energy consumption optimization is constructed with the adjustment range of peak valley TOU price on the demand side, unit output on the generation side, and unit startup and shutdown status as the central policy variables. **Figure 1** 1) shows the daily power consumption and operation cost scheduling analysis of the power system.
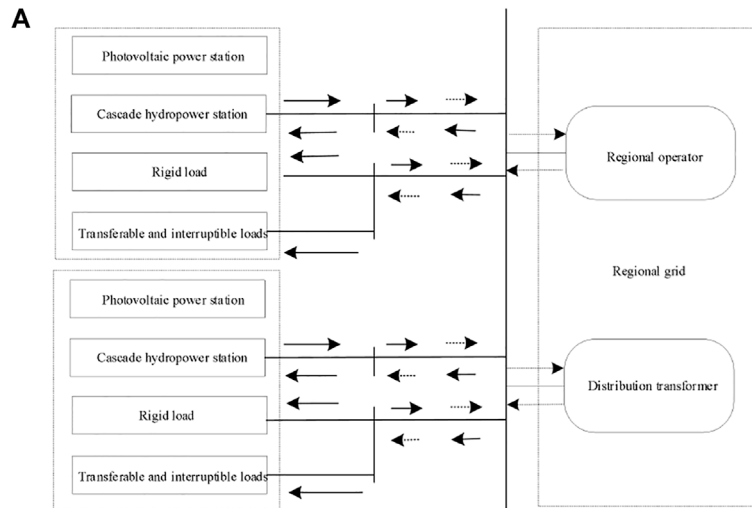
FIGURE 1 | Schematic diagram of power system operation and dispatch. **(A)** Schematic diagram of power system power generation cycle operation. **(B)** Schematic diagram of power system joint optimization generation dispatching process.

The power system joint optimization energy-saving generation scheduling model is constructed as follows:

$$\min z_1 = \sum_{t=1}^{r} \sum_{j=1}^{g_j} \left[u_j f_j(g_{ji}) + u_{jt}(1 - u_{j,t-1}) SC_{jt} \right.$$
$$\left. + u_{j,t-1}(1 - u_{jt}) SD_{jt} \right]. \tag{21}$$

$$s.t. \sum_{j=1}^{J} u_{jt} g_{jt}(1 - \theta_j) = G_i^{(0)}. \tag{22}$$

$$\sum_{j=1}^{J} g_j^{\max}(1 - \theta_j) \geq G_t^{(0)} + R_t^{(0)}. \tag{23}$$

$$f_j\left(g_{jt}\right) = a_j g_{jt}^2 + b_j g_{jt}. \tag{24}$$

$$u_{jt} g_j^{\min} \le g_{jt} \le u_{jt} g_j^{\max}. \tag{25}$$

$$\Delta g_j^- \le g_{jt} - g_{j,t-1} \le \Delta g_j^+. \tag{26}$$

$$\left(T_{j,t-1}^{on} - MT_j^{on}\right)\left(u_{j,t-1} - u_{jt}\right) \ge 0. \tag{27}$$

$$\left(T_{j,t-1}^{off} - MT_j^{off}\right)\left(u_{jt} - u_{j,t-1}\right) \ge 0. \tag{28}$$

In the formula, u_{jt} indicates the state variable value of the generator t set at the second time t. The initial startup state is set as 1 and the initial shutdown state as 0; g_{jt} represents the maximum output value of the generator set at the second time t; $f_j\left(g_{jt}\right)$ represents the total coal consumption of the unit at time (Wang et al., 2016) t; a_j and b_j represents the corresponding start-up parameters; SC_{jt} indicates the shutdown parameters; and SD_{jt} represents coal consumption. **Formula 20** makes the system t generation power value reach the target balance. At this time, it is expressed as the average power consumption rate of the second generator set (Calzarossa et al., 2018); θ_j**Formula 21** is used to dispatch the standby power of the system, $g_j^{\max}$ represents the maximum power output t of the generator set; Δg_j^- represents the power requirements required for system power generation at the second t time before dispatching; Δg_j^+**Formula 22** is used to dispatch the power output of the system t, indicating the minimum output of the generator set; $T_{j,t-1}^{on}$**Formula 23** the unit carries out climbing scheduling for the system, indicating the maximum rising and falling power limits of the generator unit; MT_j^{on} **Eqs 24**, **25** carry out the shortest start-up scheduling for the system, indicating that the operation t $t-1$ time of the generator unit at the time and the shortest operation time that can be borne; $T_{j,t-1}^{off}$ **Eqs 26–28** schedule the minimum shutdown time $t-1$ of the system, MT_j^{off} which represents the shutdown time $t-1$ of the generator unit at time, and u_{jt} the minimum shutdown time that the unit can bear.

In order to further ensure the scheduling quality, a secondary constraint of the decision variable (Kadota et al., 2018) on the scheduling model (Bhattacharya et al., 2019) g_{it} is established, and the expression formula is

$$\Delta z = z_1 - z_2. \tag{29}$$

$$\beta_{coal}^{(0)} = z_1 \Big/ \sum_{i=1}^{I}\sum_{k=1}^{K}\sum_{t=1}^{T} D_{ikt}^{(0)}. \tag{30}$$

SIMULATION EXPERIMENT

In order to verify the effectiveness of the proposed scheduling model and method, two different power system generation environments are set, summer and winter, respectively. The power system consists of one with four hydropower stations and three thermal power generating units. The typical test system is used for calculation and analysis. The total installed capacity of the system is 297.5 mw. The average power consumption rate of the power generation side of the hydropower station and thermal power plant is 80%. The maximum power load is 300 MW, and the minimum power load is 150 MW. The population size of the two algorithms is 40, and the maximum number of iterations is 1,000.
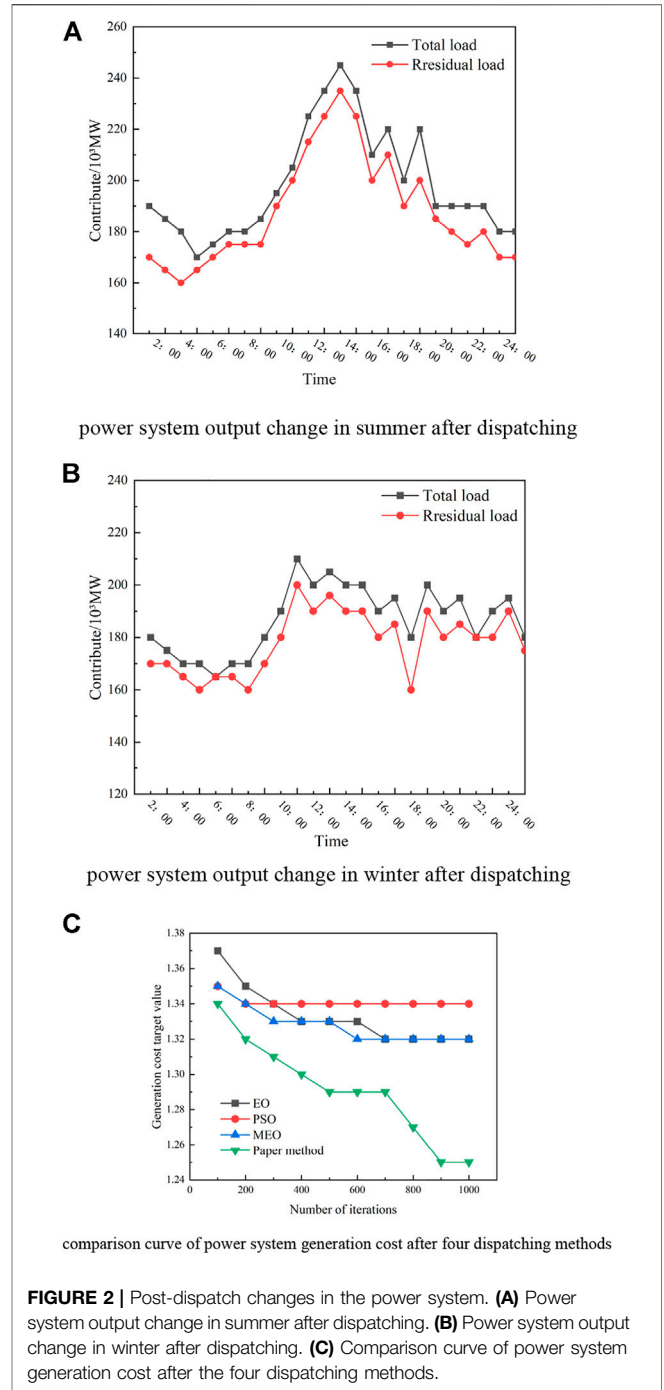
power system output change in summer after dispatching

power system output change in winter after dispatching

comparison curve of power system generation cost after four dispatching methods

FIGURE 2 | Post-dispatch changes in the power system. **(A)** Power system output change in summer after dispatching. **(B)** Power system output change in winter after dispatching. **(C)** Comparison curve of power system generation cost after the four dispatching methods.

It can be seen from **Figures 2A,B**, the generation scheduling model proposed in this article can make full use of the internal adjustability of power system generator units, effectively reduce the peak valley difference of load, and make the residual load more stable. After power generation dispatching, the mean square deviation of the load is greatly reduced, and the peak valley difference is significantly reduced. In summer, the original power generation load variance is 256.813/mw. After effective dispatching, the residual power generation load variance is reduced to 197.265/mw, and the power generation load drop difference is 26.31%.

TABLE 2 | Target value of power system generation cost obtained by the four methods.

Algorithm	Average value	Minimum	Maximum value	Standard deviation
EO	130000	129959	130500	82
PSO	137000	139059	132500	154
MEO	125000	122459	131540	45
Paper method	129920	129908	130059	15

From **Figure 2**, the power generation cost of this method is the lowest among them, and the computational robustness is better than that of the particle swarm optimization algorithm. When the number of scheduling iterations is 600, the cost target value in this study is about 1.290, while the target values of the other three methods are 1.332, 1.338, and 1.348, respectively, which are higher than those in this study. The overall cost value of the EO method shows a flat trend, indicating that the cost has not been improved after iteration. Among all methods, the declining trend of this method is the most obvious. After power generation dispatching, the cost improvement phenomenon is the best.

The dispatching results of the four comparison algorithms on the target value of power generation cost of the power system are shown in **Table 2**.

Through the comparison of the maximum values in **Table 2**, it can be seen that this study is 130,059, and the other three methods are 130,500, 132,500, and 131,540. This study is the lowest among them, and the scheduling performance is the best. Compared with the lowest value, this study is 129,908, and the other three methods are 129,959, 139,059, and 122,459. This study is still the lowest value. Through comprehensive comparison, this study performs the best.

CONCLUSION

In this article, a power system joint optimal generation scheduling method based on the improved balance optimizer is proposed, and the following conclusions are drawn:

1) Through the establishment of conditional constraint function including the concept of objective, the effective constraint on the power load climbing event is realized, which greatly reduces the subsequent calculation error caused by misjudgment and improves the quality of dispatching.
2) Based on the current comprehensive power saving policy and the premise of safety core, this study also establishes the power system joint optimization generation scheduling model, which fundamentally solves the problems of high power generation cost and high power generation energy consumption.
3) After adopting this method, the cost is reduced from the initial USD 131225/h to USD 129920/h, and the power load is also reduced from 254.78/mw to 205.36/mw. This method has high practical value.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material. Further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

JX and YT conceived and designed the calculations and experiments; YQ and AL performed the simulation; GX contributed analysis tools; JX and YT wrote the manuscript.

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