Research on Demand Side Response System of Electricity Price Under Electricity Market Incentive Mechanism

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Abstract

Aiming at the traditional day-ahead dispatching scheme of power generation, the paper proposes a power system security optimization dispatching model that considers the demand response of electricity prices under the electricity market incentive mechanism. Based on the peak and valley time-of-use electricity price, the paper establishes an incentive compensation mechanism to encourage users to be active. Participating in demand-side resource scheduling makes the effect of "peak shaving and valley filling" more pronounced. Simultaneously, to rationally configure the reserve capacity of grid operation, the system incorporates the expected power outage loss into the proposed model to ensure the grid operation safety. The analysis of calculation examples based on IEEE24 nodes shows that the power optimal dispatch model proposed in the paper considering demand response and expected outage loss

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can reduce the operating cost of the power grid under the premise of ensuring a certain level of reliability and realize the economy of the power system in the market environment and safe operation.

Keywords: Electricity market, incentive mechanism, incentive compensation, expected outage loss, electricity price demand-side response.

1 Introduction

With the gradual adjustment of the national economic structure, society's power consumption continues to rise. The peak power consumption is continually being refreshed, and the peak-to-valley difference of the power grid is gradually expanding [1]. When an accident occurs in the power grid, demand-side resources can provide timely feedback to reduce electricity demand and achieve the supply and demand balance between source and load through the use of advanced measurement technology and communication systems.

Based on the existing research, this paper integrates demand response and reliability indicators into the day-ahead dispatch of the power system, establishes a power optimal dispatch model that considers dynamic incentive compensation and expected outage losses, and coordinately solves the unit commitment problem on the generation side and the demand side. The problem of interaction between supply and demand to realize the economy and safety of grid operation. Finally, the analysis based on the example of the IEEE-RTS24 node verifies the effectiveness of the method in this paper.

2 Demand Response Behavior Modeling Based on the Dynamic Incentive Compensation Mechanism

A dynamic incentive compensation mechanism is introduced to build a combined demand response model under multiple periods, encouraging users to reduce power demand during load peaks to ensure grid safety [2]. Figure 1 describes the framework of demand response participation in power system dispatch.

During peak hours of electricity consumption, the higher the incentive compensation, the stronger the users' initiative to participate in demand response, and the greater the degree of participation in demand response.

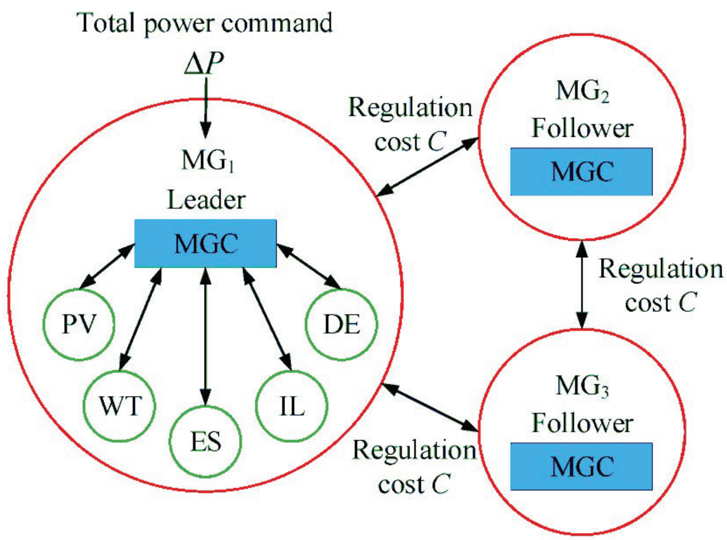

Figure 1 Power dispatch planning framework with DR.

2.1 A Single-period Demand Response Model

Single-period demand response means that during a specific period, under the action of electricity prices or incentives, users actively reduce their load but cannot transfer their electricity demand to other periods [3]. After implementing demand response, the user's power demand during t period will be adjusted from D_t^0 to D_t^{DR}, then

$$\Delta D_t = D_t^{DR} - D_t^0 \tag{1}$$

Where ΔD_t is the load difference before and after the demand response. Assuming that the system has the highest load, the grid company will give users A^* yuan/MWh incentive compensation, as the load level of each period different, the incentive price will be dynamically adjusted. Here, define the "demand proportional coefficient" Γ_t as the ratio of the load to the maximum load in each period, namely

$$\Gamma_t = \frac{D_t^0}{\max\{D_\tau^0\}}, \tau \in \{1, 2, \ldots, t, \ldots, T\}, \tag{2}$$

Where T is the total number of periods. Then the dynamic incentive compensation price A_t of each period is

$$A_t = A^* \Gamma_t, \tag{3}$$

Where T is the total number of periods. Then the dynamic incentive compensation price $A^*$of each period is

$$p(\Delta D_t) = A_t[D_t^0 - D_t^{DR}], \tag{4}$$

Then the demand response income S of the user in the t-th period is

$$S(D_t^{DR}) = B(D_t^{DR}) - D_t^{DR} P_{r_t} + p(\Delta D_t) \tag{5}$$

Among them: $B(D_t^{DR})$ is the revenue when the user demand is equal to D_t^{DR} before the incentive compensation is implemented in the t-th period; P_{r_t} is the electricity price in the t period during the demand response. The user revenue $B(D_t^{DR})$ is mostly in the form of a quadratic function, namely

$$B(D_t^{DR}) = B(D_t^0) + \mathrm{Pr}_t^0[D_t^{DR} - D_t^0] \times \left\{1 + \frac{D_t^{DR} - D_t^0}{2E_{t,t}D_t^0}\right\} \tag{6}$$

Among them: $E_{t,t}$ is the self-elasticity coefficient, Pr_t^0 is the electricity price during the t period before the demand response, and $B(D_t^0)$ is the income when the load demand is equal to D_t^0. According to Equations (5) and (6), the user's demand response income S is similar to the opening downward Parabolic function. Therefore, when $\partial S/\partial D_t^{DR} = 0$, the demand response income S is the largest, that is

$$\frac{\partial S(D_t^{DR})}{\partial D_t^{DR}} = \frac{\partial B(D_t^{DR})}{\partial D_t^{DR}} - \mathrm{Pr}_t + \frac{\partial p(\Delta D_t)}{\partial D_t^{DR}} = 0 \tag{7}$$

Substitute Equation (4) into (7) to get

$$\frac{\partial B(D_t^{DR})}{\partial D_t^{DR}} = \mathrm{Pr}_t + A^*\Gamma_t \tag{8}$$

Combining formulas (6) and (8) can be obtained

$$\mathrm{Pr}_t + A^*\Gamma_t = \mathrm{Pr}_t^0 \left\{1 + \frac{D_t^{DR} - D_t^0}{2E_{t,t}D_t^0}\right\} \tag{9}$$

Then after the demand response, the user's electricity demand in the t-th period is adjusted to

$$D_t^{DR} = D_t^0 \left\{1 + E_{t,t}\frac{\mathrm{Pr}_t - \mathrm{Pr}_t^0 + A^*\Gamma_t}{\mathrm{Pr}_t^0}\right\} \tag{10}$$

2.2 Multi-period Demand Response Model

Multi-period demand response means that under the effect of electricity prices or incentives, users transfer their electricity demand in the current period to other periods to achieve the purpose of load transfer. Similar to the derivation process of the single-period elastic load model, in the case of multiple periods, users the demand function is

$$D_t^{DR} = D_t^0 \left\{ 1 + \sum_{j=1, j \neq t}^{T} E_{t,j} \frac{\mathrm{Pr}_j - \mathrm{Pr}_j^0 + A^* \Gamma_j}{\mathrm{Pr}_j^0} \right\} \tag{11}$$

Where $E_{t,j}$ is the cross-elasticity coefficient.

2.3 Demand Response Combination Model

Considering that in actual production and operation, the necessary electricity consumption of residents and industrial and commercial users will not be reduced due to price or incentive adjustments, and some processes of industrial users cannot be transferred to other periods, so we introduce the "demand response coefficient" η as User participation in demand response projects [4]. According to the basic principles of consumer psychology, the higher the power grid's price incentive, the stronger the user's initiative to participate in demand response. Without considering the dead zone and saturation threshold, it can be considered that η_t is proportional to A_t at time t. When the incentive price is greater than the electricity price, the user will fully participate in the demand response.

$$\eta_t = \min(A_t / \mathrm{Pr}_t^0, 1) \eta_t \in [0, 1] \tag{12}$$

Combining Equations (10)–(12), the load that participates in demand response during t period is

$$D_t^{DR} = \eta_t D_t^0 \left\{ 1 + \sum_{j=1}^{T} E_{t,j} \frac{\mathrm{Pr}_j - \mathrm{Pr}_j^0 + A^* \Gamma_j}{\mathrm{Pr}_j^0} \right\} \tag{13}$$

The actual load during t period is

$$D_t = (1 - \eta_t) D_t^0 + D_t^{DR} \tag{14}$$

3 Reliability Index Calculation

There are two leading reliability indicators mentioned in this article: the probability of loss of load (LOLP); the other is the expected value of insufficient power (EENS). In the traditional sense, LOLP refers to the probability that the available capacity of a generator set does not meet a particular load demand in the market environment; the smaller the LOLP, the more abundant the power supply, and the closer the power market is to a perfectly competitive market. Therefore, the limit of LOLP can be set to promote competition in the market and improve the power grid's security [5]. Simultaneously, in this article, the model introduces the expected power outage loss in the objective function, thereby transforming the reliability index EENS into an economic index to realize the quantitative processing of the reliable operation of the power grid. To simplify the model, it is assumed that the failure of the generator set only causes the power grid loss. The failure outage rate can be replaced by the forced outage rate (FOR). Considering that the probability of multiple failures of the unit is minuscule under the condition of day-ahead scheduling, the large number of units will cause the calculation amount to increase exponentially, so this article calculates LOLP EENS When, only double failures are considered. If all units are working normally during t period as state ε_t^0, the probability $P[\varepsilon_t^0]$ that the system is in state ε_t^0 is

$$P[\varepsilon_t^0] = P_t^0 = \prod_{i=1}^{N_{Gen}} (1 - \gamma_{i,t} U_i) \tag{15}$$

Similarly, if a unit i fails in the t period, then

$$P[\varepsilon_{i,t}^1] = p_{jk,t}^1 = \gamma_{i,t} U_i \prod_{j=1, j \neq i}^{N_{Gen}} (1 - \gamma_{j,t} U_j) \tag{16}$$

If two units j and k fail in period$t$, there are

$$P[\varepsilon_{jk,t}^2] = p_{jk,t}^2 = \gamma_{j,t} \gamma_{k,t} U_j U_k \prod_{i=1, i \neq j,k}^{N_{Gen}} (1 - \gamma_{i,t} U_i) \tag{17}$$

3.1 Loss of Load Probability (LOLP)

In this article, LOLP can be regarded as a powerful means to improve the spinning reserve. By limiting the LOLP to a certain acceptable level, the grid company can adjust the reserve capacity according to the power generation side resources' characteristics and strengthen the power grid's ability to withstand accidents [6]. After a fault occurs, the system will not lose load when there is sufficient reserve. To calculate the LOLP, this paper introduces a 0–1 variable δ to represent the power grid's load loss state. When only one unit fails, $\delta_{j,t}$ satisfies the following linear unequal relationship:

$$\frac{D_t - \sum_{i=1,i\neq j}^{N_{Gen}}(P_{i,t}+R_{i,t})}{\sum_{i=1}^{N_{Gen}} P_{i,t}^{\max}} \leq \delta_{j,t} \leq 1 + \frac{D_t - \sum_{i=1,i\neq j}^{N_{Gen}}(P_{i,t}+R_{i,t})}{\sum_{i=1}^{N_{Gen}} P_{i,t}^{\max}} \tag{18}$$

Among them: $\delta_{j,t} = 1$ indicates that the switch of unit j during t period will lead to insufficient reserve and system load loss. When $D_t > \sum_{i=1,i\neq j}^{N_{Gen}}(P_{i,t} + R_{i,t})$, the lower bound of formula (18) is in the interval (0,1), and the upper bound is in (1,2), so $\delta_{j,t} = 1$; On the contrary, the upper and lower bounds of formula (18) are in the interval (0,1) and $(-1, 0)$ respectively, $\delta_{j,t} = 0$, that is, the system is in a safe state and will not lose load. Similarly, when two units fail and stop $\delta_{jk,t}$ satisfies the following linear inequality relationship:

$$\frac{D_t - \sum_{i=1,i\neq j,k}^{N_{Gen}}(P_{i,t}+R_{i,t})}{\sum_{i=1}^{N_{Gen}} P_{i,t}^{\max}} \leq \delta_{jk,t} \leq 1 + \frac{D_t - \sum_{i=1,i\neq j,k}^{N_{Gen}}(P_{i,t}+R_{i,t})}{\sum_{i=1}^{N_{Gen}} P_{i,t}^{\max}} \tag{19}$$

Then the load loss probability $LOLP_t$during t period can be expressed by the following formula:

$$LOLP_t = \sum_{i=1}^{N_{Gen}} \delta_{i,t} s_{i,t}^1 p_{i,t}^1 + \sum_{i=1}^{N_{Gen}} \sum_{j>i}^{N_{Gen}} \delta_{ij,t} s_{ij,t}^2 p_{ij,t}^2 \tag{20}$$

Among them, $s_{i,t}^1$ and $s_{ij,t}^2$ are the load loss contribution coefficients of unit i under single and dual unit failures respectively. Under single unit failure conditions, the power supply shortage is only caused by the shutdown of unit i, so $s_{i,t}^1 = 1$; under dual unit failure conditions, the larger FOR The unit is more likely to fail, and the larger capacity unit will cause a larger load gap than the smaller capacity unit, so $s_{ij,t}^2$ can be expressed by the following formula:

$$s_{ij,t}^2 = \frac{(P_{i,t}+R_{i,t})p_i}{(P_{i,t}+R_{i,t})p_i + (P_{j,t}+R_{j,t})p_j} \tag{21}$$

3.2 Low Battery Expected Value $(EENS)$

It is another indicator to measure the reliability of the power grid. It can be used to measure the current reserve capacity level of the system. When $EENS$ is small, the reserve capacity is larger, and the user's power demand is guaranteed in the event of a failure. This article assumes that the power grid the expected loss of load $(ELNS)$ remains unchanged from D. It can be seen from $EENS = ELNS.\Delta T$ that in the same period of time, $EENS$remains constant. In this paper, $\Delta T = 1h$ is taken. Under the condition of the obtained $LOLP_t$, the expected value of insufficient power caused by the unit failure during t period $EENS_t$ can be expressed as

$$\begin{aligned} EENS_t = &\sum_{i=1}^{N_{Gen}} \delta_{i,t} s_{i,t}^1 p_{i,t}^1 (P_{i,t} + R_{i,t} - SR_t) \\ &+ \sum_{i=1}^{N_{Gen}} \sum_{j>i}^{N_{Gen}} \delta_{ij,t} s_{ij,t}^2 p_{ij,t}^2 (P_{i,t} + R_{i,t} + P_{j,t} + R_{j,t} - SR_t) \end{aligned} \tag{22}$$

Among them: $SR_t = \sum_{i=1}^{N_{Gen}} R_{i,t}$ is the spinning reserve capacity of the system during the t period, and $R_{i,t}$ is the reserve capacity of the unit i during the t period. Through surveys and statistics on users, the unit load loss (VOLL) is obtained to convert the reliability index EENS into an economic index to achieve the mutual balance between reliability and economy in the operation of the power grid the market environment.

4 A Power Dispatch Model That Takes Into Account Demand Response and Reliability Constraints

According to China's current electricity price system, this article introduces an incentive mechanism based on time-of-use electricity prices to guide users to cut peaks further and fill valleys. Considering that in the case of insufficient reserve capacity, when the grid fails, it may affect the average production of users. Therefore, this paper proposes a unit combination method that takes into account the demand response and user power outage losses [7]. The core is that the sum of the grid operating cost and the expected power outage loss are minimized, which indirectly maximizes social benefits and will be reliable Performance indicators. Risk levels and benefits are directly constrained to realize automatic backup configuration in power dispatch.

4.1 Objective Function

According to the above analysis, the objective function of the model in this paper is

$$\min \sum_{t=1}^{T} \sum_{i=1}^{N_{Gen}} \gamma_{i,t}(SU_{i,t} + Cost_{i,t}^{Gen}) + \sum_{t=1}^{T} Cost_t^{Inc} + \sum_{t=1}^{T} ECost_t \quad (23)$$

$$Cost_{i,t}^{Gen} = a_i P_{i,t}^2 + b_i P_{i,t} + c_i \quad (24)$$

$$Cost_i^{Inc} = A^* \Gamma_t (D_t^0 - D_t) \quad (25)$$

$$ECost_t = VOLL * EENS_t \quad (26)$$

Among them: $SU_{i,t}$ is the start-up cost of the generator; $Cost_{i,t}^{Gen}$ is the operating cost of the generator, generally in the form of a quadratic function; $P_{i,t}$ is the output of the generator i in the period t; a_i, b_i, c_i is the operating cost parameter of the unit; $Cost_i^{Inc}$ is the payment to the grid company Participate in the incentive compensation of DR users.

4.2 Model Constraints

4.2.1 System constraints

(i) Power balance constraints

$$\sum_{i=1}^{N_{Gen(b)}} P_{i,t} - D_{b,t} = \sum_{l=1}^{L_b} F_{l,t}, \forall b, \forall l \quad (27)$$

Among them: $N_{Gen(b)}$ is the total number of generator sets connected to bus b, $D_{b,t}$ is the power demand of bus b at time t, and L_b is the number of branches connected to bus b. The left side of the equal sign in Equation (27) is the implementation demand After the response, the net input power of bus b at time t, and the right side of the equal sign is the sum of the branch power flow connected to bus b at time t. The branch power flow $F_{l,t}$ can be calculated using DC power flow, namely

$$F_{l,t} = \frac{1}{X_l}(\delta_l^s - \delta_l^r), \forall t, \forall l \quad (28)$$

Among them: δ_l^s, δ_l^r is the phase angle of the bus nodes at both ends of branch l; X_l is the impedance of branch l.

(ii) The branch flow constraint.

The power flow of each branch in the power grid should be within the limit, namely

$$F_{l,t} =\leq |F_{l,t}^{\max}| \forall t, \forall l \tag{29}$$

Where $F_{l,t}^{\max}$ is the maximum value of the current on branch l at time t.

4.2.2 Crew constraints

(i) The upper and lower limits of the output power of the generator set

$$P_i^{\min} \gamma_{i,t} \leq P_{i,t} \leq P_i^{\max} \gamma_{i,t}, \forall i, \forall l \tag{30}$$

Among them, $P_i^{\max}$ and $P_i^{\min}$ are the upper and lower limits of unit i's output.

(ii) Unit start and stop constraints

$$\begin{cases} (\gamma_{i,t-1} - \gamma_{i,t}) \times (X_{i,t-1}^{on} - T_i^{on}) \geq 0 \\ (\gamma_{i,t} - \gamma_{i,t-1}) \times (X_{i,t-1}^{off} - T_i^{off}) \geq 0 \end{cases} \tag{31}$$

Among them: $X_{i,t-1}^{on}$ and $X_{i,t-1}^{off}$ are the number of periods during which the generator set i has been continuously started and stopped during the period $t-1$, and T_i^{on} and T_i^{off} are the minimum number of periods of start and stop of the generator i, respectively.

(iii) Crew climbing constraints

$$\begin{cases} P_{i,t}\gamma_{i,t} - P_{i,t-1}\gamma_{i,t-1} \leq P_i^{up} \\ P_{i,t-1}\gamma_{i,t-1} - P_{i,t}\gamma_{i,t} \leq P_i^{down} \end{cases} \tag{32}$$

Among them, P_i^{up} and P_i^{down} are the unit's i up/down ramp rate limit respectively.

4.2.3 Security constraints

(i) System backup constraints

$$\sum_{i=1}^{N_{Gen}} \gamma_{i,t} P_i^{\max} \geq SR_t + D_t \tag{33}$$

(ii) Reliability constraints.

The reliability constraints of power grid operation are mainly reflected in the loss of load probability (LOLP) and the expected value of insufficient power (EENS) in each time period are less than a certain limit, namely

$$LOLP_t \le LOLP^{\max} \tag{34}$$

$$EENS_t \le EENS^{\max} \tag{35}$$

Among them: $LOLP_t$ is the probability of loss of load during t period, $LOLP^{\max}$ is the limit of the probability of loss of load; $EENS_t$ is the expected value of insufficient power during t period and $EENS^{\max}$ is the expected value of maximum insufficient power.

5 Case Analysis

This paper takes the IEEE-RTS24 node 26 machine system as an example to analyze the above model. The detailed data of the system can be seen in the literature. The analysis shows that the model in this paper is a mixed-integer programming problem (MIP), using existing commercial software. It can be solved quickly and effectively [8]. This paper uses YALMIP to call the solver Gurobi to program in Matlab2015a to solve the established unit commitment model. The paper selects the weekend of 44–52 weeks in winter as a typical day, and its load forecast curve is shown in Figure 2.

The time and electricity price of each period are shown in Table 1. The demand price elasticity coefficient of load is shown in Table 2.

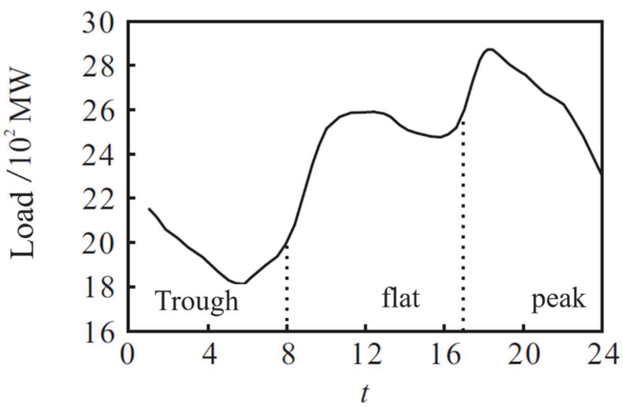

Figure 2 A typical daily load forecast.

Table 1 Time-of-use electricity price and time division

Load Condition	Time Period	Electricity Price/(Yuan/MWh)
Valley	0:00−8:00	305
level	8:00−17:00	615
peak	17:00−24:00	1025

Table 2 Demand price elasticity coefficient

E	Valley	Level	Peak
Valley	−0.1	0.01	0.055
level	0.01	−0.1	0.012
peak	0.055	0.012	0.16

Table 3 Cost comparison under different incentive modes

Mode	Incentive Price/ (Yuan/MWh)	Power Generation Cost/Yuan	Incentive Cost/Yuan	Total Cost/Yuan	Percentage of Total Cost Reduction/%
1	0	5750007	0	5750007	0
2	400	5315987	184789	5500776	4.33
3	550	5201636	205363	5406999	5.97
4	700	5126578	203905	5420483	5.56
5	850	5099117	490594	5589711	2.79

5.1 Day-ahead Scheduling that Only Includes Demand Response

This article introduces DR into the day-ahead dispatch model of the power system, so it is necessary to study the adjustment of DR to day-ahead dispatch. This article's demand response project is to establish an incentive compensation mechanism based on the time-of-use electricity price. Adjust the incentive price to guide users to cut peaks and fill valleys. The following five incentive modes are analyzed to study the impact of incentive prices on day-ahead scheduling, as shown in Table 3. The incentive price of mode 1 is 0. That is, it is not considered the primary operating mode of DR and reliability indicators; the incentive prices of mode 2 and mode 5 are 400, 550, 700, and 850/(yuan/MWh) respectively.

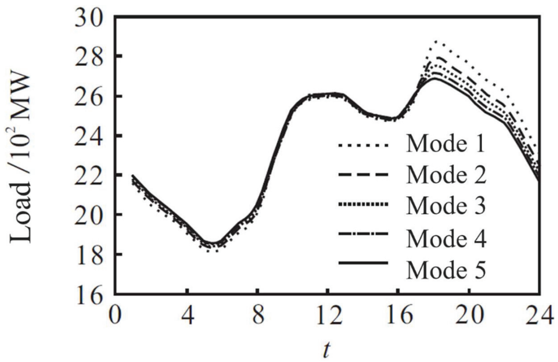

Figure 3 Comparison of load changes under different excitations.

Figure 3 shows the demand response results of all loads in the system under different incentive prices. It can be seen from Figure 3 that compared to the primary operating mode (mode 1), the power demand of mode 2 to mode 5 during peak hours is all as a result, the load during normal and valley periods increased slightly. This is due to the design of a dynamic incentive mechanism in this paper. During peak electricity consumption, the incentive price is higher, and users are driven by the price to actively reduce or transfer the load, thereby achieving peak shaving. Therefore, the higher the incentive price, the stronger the user's initiative to participate in demand response, and the full-time load curve will therefore be improved.

Table 3 compares the costs under different incentive prices, where the cost of power generation includes unit start-up costs and fuel costs. As can be seen from Table 3, as the incentive price continues to increase, the total incentive cost continues to rise, but the cost of power generation continues. Therefore, the total cost presents a U-shaped trend of "decreasing first and then increasing," so there is an incentive price that minimizes the total cost of the system's day-ahead scheduling. It can be obtained by optimizing the incentive price; when the incentive price is 584.12/(Yuan/MWh), the total cost is the smallest, 5374458 yuan, which is about 6.53% lower than the total cost of Mode 1. The total cost reduction under the optimal incentive price is limited, which is due to the peak-to-valley difference of the load curve after the implementation of DR Reduced, the unit avoids frequent start-ups, and the cost of power generation decreases, but due to the need to pay a certain incentive fee to users, the total cost advantage under the optimal incentive price is not very obvious [9].

Table 4 The impact of reliability indicators on day-ahead scheduling costs

Mode	Generation Cost	Incentive Cost	Expected Power Outage Loss	Total Cost
6	5133876	240582	0	5374458
7	5185987	240582	236974	5663543
8	5750007	0	485416	6235423

Table 5 Comparison of reliability indicators

Mode	$\max_{t\in T}(LOLP_t)/\%$	$\max_{t\in T}(EENS_t)/MWh$
6	8.45	3.97
7	4.71	2.31
8	10.27	6.85

5.2 Day-ahead Scheduling Considering Demand Response and Reliability Indicators

It can be seen from the previous section that after considering DR in the traditional day-ahead scheduling plan, the load curve has been optimized, and the total system operating cost has also been reduced. After the reliability index is included in the day-ahead scheduling, considering that the unit failure and shutdown may cause load loss, to ensure the safe operation of the system and the unaffected power demand of residents, the level of spare capacity will increase accordingly, which will lead to an increase in the total operating cost.

Now set $LOLP^{\max} = 5\%$, $EENS^{\max} = 2.4$ MWh, VOLL = 5000 yuan/MWh, when the incentive price is 584.12 yuan/MWh, the results are shown in Tables 4 and 5, where mode 6 means that only DR is considered Operating mode, mode 7 represents the day-ahead scheduling operation mode that considers both DR and reliability indicators.

It can be seen from Table 4 that under the optimal incentive price, the demand response participation of users in Mode 6 and Mode 7 remains unchanged, and the incentive cost is the same. After the reliability index is incorporated into the overall consideration of the day-ahead scheduling, Mode 7 Compared with only considering DR, the total cost has increased correspondingly, but compared with Mode 8, the economy is still guaranteed. Mode 8 does not consider the impact of user-side demand response, and it expects that the power outage loss will increase significantly, which will lead to a further increase in the total cost.

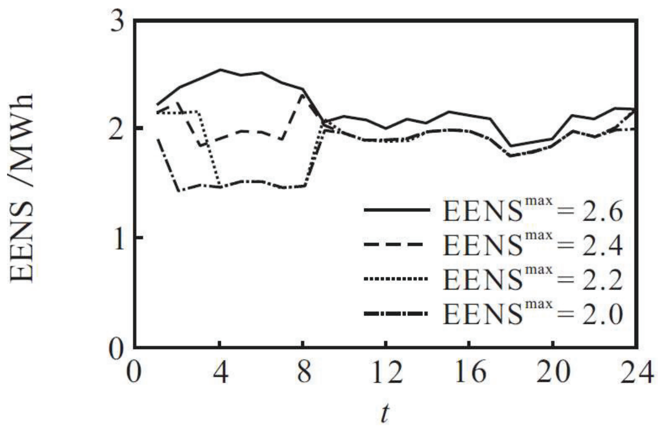

Figure 4 The influence of $EENS^{\max}$ on EENS in each period.

Table 5 shows that after taking into account DR and reliability indicators (i.e., mode 7), the maximum value of the loss of load probability (LOLP) and the maximum expected value of insufficient power (EENS) of the system in each period are significantly reduced, reflecting the model of this paper. Effectiveness [10]. Comprehensively shown in Tables 4 and 5, compared with the literature, the model proposed in this paper shows superiority in both the total cost and the reliability index, thus achieving a balance between economy and reliability. Good balance.

5.3 The Impact of the Expected Value of Insufficient Maximum Power on the Optimization Results

It can be seen from the analysis that when $EENS^{\max}$ is different, the standby level of the system is also different, which in turn affects the cost of power generation and the expected blackout loss. In the case of $LOLP^{\max} = 5\%$, VOLL = 5000 yuan/MWh, and the incentive price of 584.12 yuan/MWh, this article Further study on $EENS^{\max}$, as shown in Figure 4.

It can be seen from Figure 4 that as $EENS^{\max}$ gradually decreases, the EENS of each period also decreases accordingly. When A decreases from 2.6 MWh to 2.4 MWh, the EENS of the whole period decreases, and 2:00am-7: The decrease was obvious during the 00am time period. When $EENS^{\max}$ decreased from 2.4 MWh to 2.0 MWh, EENS remained basically constant during the period of 9:00am-24:00pm, but the EENS decreased significantly between 1:00am-8:00am. In summary, During the valley period,

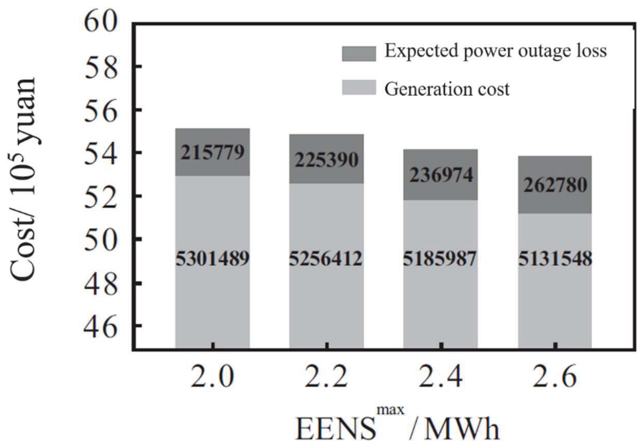

Figure 5 Impact on economics.

due to the small load and the small number of units started, the reserve capacity remains at a low level [11]. When a unit fails and stops, it is very likely to cause load loss. By setting a reasonable level, the reserve capacity can be appropriately increased and reduced the expected value of electricity is insufficient. Figure 5 shows the impact of $EENS^{\max}$ on the economics of grid operation. From Figure 5, it can be seen that as $EENS^{\max}$ increases, the expected outage loss of the system also increases accordingly. On the contrary, the cost of power generation decreases in turn Therefore, when the power company formulates the day-ahead scheduling plan, it is necessary to reasonably select the reserve capacity according to the actual situation of the grid operation to achieve a balance between economy and reliability.

5.4 Impact of Unit Power Outage Loss on Optimization Results

In this article's model, the value of VOLL directly affects the expected power outage loss, which in turn affects the day-a-day scheduling plan. Under other conditions unchanged, the VOLL in this example is set to 4000 yuan/MWh, 5000 yuan/MWh and 6000 yuan/ MWh to study the influence of VOLL on the optimization results. Figure 6 shows the change of the system reserve capacity with VOLL.

A longitudinal comparison shows that with the increase of VOLL, each period's reserve capacity also gradually increases. This is because VOLL measures the economic loss caused by load loss [12]. The larger the VOLL, the more significant the expected power outage loss in the objective function.

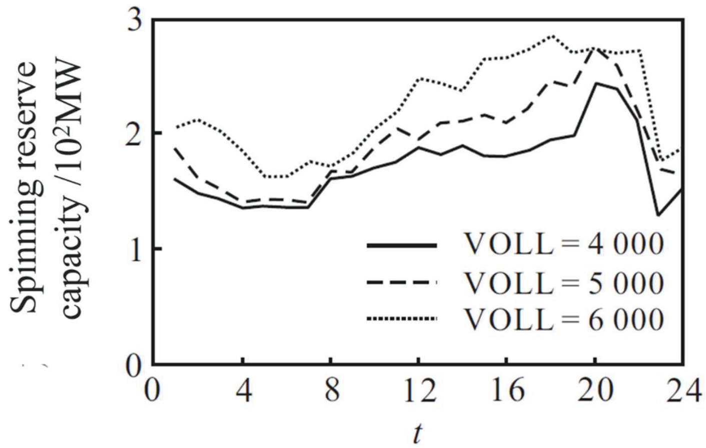

Figure 6 Spare capacity for each period under different VOLL values.

To minimize the value of the objective function, it is necessary to maintain more spare capacity and reduce the expected value of insufficient power to reduce the amount of load loss. A horizontal comparison shows that when the spare capacity is sufficient, the spare capacity during peak hours is higher than usual. The segment and valley periods are more prominent because there are more operating units during peak hours. When a unit fails, other units can quickly fill the loading gap, limiting the load loss expectation within a specific range. According to the load level, this paper's model can dynamically adjust the spinning reserve capacity to ensure system operation safety.

6 Conclusion

The model's characteristic in this paper is that demand response is integrated into the traditional day-ahead dispatch unit combination problem, and a dynamic incentive response mechanism is established based on the time-of-use electricity price. This paper uses the power grid's characteristic probability information to convert the reliability index into the economic index and realizes the effective unity of the power system operation's economy and safety. Through the analysis of examples, it can be found that objective factors such as reliability indicators and VOLL levels have an important impact on the power system's reserve capacity and operating costs. When formulating the day-ahead dispatch plan, the power company can maximize economic and safety benefits by setting reasonable reliability indicators.

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Biography

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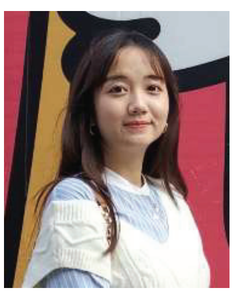

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