Optimization strategy of price-based demand response considering the bidirectional feedback effect

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Abstract
Time of use pricing strategy can not only reduce the load fluctuation but also improve the power system reliability. Generally, before carrying out a time of use pricing optimization, it needs to perform a period partition optimization for dividing peak-valley periods. In existing researches, however, the period partition optimization and the time of use pricing optimization are implemented independently. Although the output of period partition optimization is used as the input of time of use pricing optimization, the bidirectional feedback effect between period partition optimization and time of use pricing optimization is not considered, which will lead to the existing time of use pricing optimization may not be the globally optimal solution. Therefore, this paper investigates a new optimization method for time of use pricing optimization with the consideration of bidirectional feedback effect, establishes a comprehensive customer satisfaction degree model considering the customer load proportion coefficient, and defines an elastic cofactor to describe the electricity price response difference of multiple types of customers. The Roy Billinton test system is used to verify the correctness and effectiveness of the proposed method in this paper.

1 | INTRODUCTION

As one of demand response strategies of power system, the TOU pricing strategy takes advantage of customers’ response to the different periods’ electricity price [1–2], realizes the peak shaving and valley filling [3–4], and reduces the fluctuation of load curve to improve the reliability of the power system [5]-[6]. Generally, the TOU pricing strategy is divided into two steps: the period partition optimization (PPO) and the TOU pricing optimization (TPO). The former divides the typical daily load into peak-flat-valley periods and the latter calculates the electricity price sequence by constructing a suitable TOU optimization model. It can be seen from Figure 1 that the output of PPO is used as the input of TPO, but both are independent optimization, that is PPO and TPO are executed separately in order. Although there is a one-way information transmission from PPO to TPO, PPO is not adjusted for making TPO better, and the output of TPO is also not fed back to PPO which will lead to the overall optimization may not be the global optimum. Therefore, the strategy design for electricity price-based demand response needs to consider the bidirectional feedback effect between PPO and TPO in order to achieve the global optimality. The bidirectional feedback effect includes the information transmission of both “PPO to TPO” and “TPO to PPO”. Meanwhile, the comprehensive customer satisfaction should also be considered in the TOU pricing optimization for improving the customer satisfaction.

At present, there have many studies on the period partitioning algorithm in TOU pricing optimization. Refs. [7–9] discuss cost optimization schemes of the electric vehicle and customer demand response considering TOU strategy. However, the period partitioning results were directly given by fixed periods without optimization and used as the input of TOU pricing optimization. But the above optimization process has the
The following disadvantages: (1) The period partitioning optimization is not implemented and it may cause that the results do not match the actual load level; (2) It only considers the one-way information transmission from PPO to TPO while the feedback effect of TPO to PPO has not been taken into account. Refs. [10, 11] propose the period partitioning algorithms based on an equal-step enumeration iteration technique and a boundary moving technique, respectively, and the latter has a significant improvement over the former in the period partitioning efficiency. However, the overall optimization may not be the global optimum due to the lack of the bidirectional feedback effect in the above two methods. In summary, in existing researches, the period partition optimization and the TOU pricing optimization are often treated as two independent optimization processes. In fact, both the period partition and the TOU pricing optimization serve the same purpose of peak shaving and valley filling, delaying investment, and improving system reliability. Thus, PPO and TPO should be an entirety, and independent optimization will inevitably lead to the result may not be global optimum. Therefore, in the design of electricity price-based demand response strategy, it is necessary to consider the bidirectional feedback effect for obtaining a more optimal solution.

Refs. [12–14] investigate the customer satisfaction model by the load change before and after carrying out demand response. But the model does not take into account the customer's satisfaction of the current electricity expenditure. Refs. [15, 16] discuss the satisfaction degree (SAD) based on the customer's electricity energy expense, and design weight coefficients for different types of customers, which can describe the customer's satisfaction on the current TOU strategy, but it does not consider the impact of multiple types of customers in one area. Therefore, this paper proposes a comprehensive customer satisfaction model that takes into account the customer's load proportion coefficient, which can not only reflect the customer satisfaction of electricity energy expense, but also consider the multiple types of customers.

In summary, this paper mainly investigates the electricity price-based demand response optimization problem with the integration of the bidirectional feedback effect, and presents a SAD model considering the load proportion coefficient. In addition, an elastic cofactor is defined for describing the electricity price response difference of multiple types of customers. A conceptual framework of resilience domains and its measurement approaches is proposed in Ref. [17], and it analyses the conceptual difference of resilience and reliability of power systems. Ref. [18] presents the inverse problem of reliability evaluation in power systems to obtain unknown component's parameters from the known system reliability indices. Ref. [19] proposes a reliability modelling and assessment method for the power information system (i.e., cyber space in power system). So, the reliability of power system in this paper is also investigated to analyse the influence of considering the bidirectional feedback effect, and the Roy Billinton test system (RBTS) [20] is used to verify the feasibility and effectiveness of the proposed model and technique in this paper.

The main contributions of this paper are as follows:

1. This paper presents an electricity price-based demand response optimization method considering the bidirectional feedback effect, which can overcome the deficiency of the one-way information transmission method, and achieve the global optimality.
2. An elastic cofactor integrated in the price elasticity matrix is presented for not only directly reflecting the impact of electricity price on customer's electrical energy consumption, but also effectively describing the electricity price response difference of multiple types of customers.
3. The SAD model considering the load proportion coefficient is proposed in this paper. An objective function of electricity price optimization problem considering the comprehensive satisfaction is constructed.

The remaining parts of the paper are organized as follows. Section 2 presents the price elasticity matrix of demand considering the elastic cofactor. Section 3 proposes the comprehensive customer satisfaction model which takes into account the customer's load proportion coefficient and describes the TOU price optimization method considering bidirectional feedback effect. Case studies are presented in Section 4. Section 5 concludes the paper.

2 | ELECTRICITY PRICE ELASTIC MATRIX MODEL CONSIDERING AN ELASTIC COFACTOR

Implementing TOU strategy will lead to the deviation of prices in peak, flat, and valley periods, and the customer will respond the price difference, which can be described by the price elasticity matrix [21, 23]. Considering that the electricity price response difference for different types of customers and complication of obtaining the corresponding elastic matrix, this paper proposes an elastic cofactor to describe the response difference.

2.1 | Price elasticity matrix considering an elastic cofactor

The elasticity matrix can be divided into the self-elasticity coefficient and the cross-elasticity coefficient. The self-elasticity coefficient can be used to describe the customer's response to the
change of electricity prices during the current period, that is:

\[
\xi_{mm} = \frac{\Delta Q_m}{Q_m} \frac{p_0}{\Delta p_m}
\]  

(1)

where \( m \) is the period, \( m \in \{p, f, v\} \), and \( p, f \) and \( v \) denotes the peak, flat, and valley periods; \( Q_m \) is the consumed electricity energy in the \( m \)-th period before TOU; \( \Delta Q_m \) is the change of consumed electricity energy in the \( m \)-th period before and after TOU; \( p_0 \) is the original price; \( \Delta p_m \) is the change of electricity prices in the \( m \)-th period after TOU; \( \xi_{mm} \) is the self-elasticity coefficient.

The cross-elasticity coefficient is used to describe the customer’s response to the change of electricity prices during the non-current period, as shown in:

\[
\xi_{mn} = \frac{\Delta Q_m}{Q_m} \frac{p_n}{\Delta p_n}
\]  

(2)

where \( n \) is the period, \( n \in \{p, f, v\} \), and \( m \neq n \); \( \Delta p_n \) is the electricity price change in the \( n \)-th period after TOU.

The self-elasticity coefficient and the cross-elasticity coefficient can be used to form the electricity price elasticity matrix of TOU strategy, namely:

\[
E = \begin{bmatrix}
\xi_{pp} & \xi_{pf} & \xi_{pv} \\
\xi_{fp} & \xi_{ff} & \xi_{fv} \\
\xi_{vp} & \xi_{vf} & \xi_{vv}
\end{bmatrix}
\]  

(3)

where \( E \) is the electricity price elasticity matrix.

Therefore, according to the electricity price elasticity matrix, the electrical energy of each period after TOU can be obtained, namely:

\[
\begin{bmatrix}
\Delta Q_m \\
\Delta Q_f \\
\Delta Q_v
\end{bmatrix} = E \begin{bmatrix}
\Delta p_p \\
\Delta p_f \\
\Delta p_v
\end{bmatrix}
\]  

(4)

Generally, the electricity price elasticity matrix changes with the type of customers. Considering the complexity of obtaining historical load data which is used to reconstruct the elasticity matrix for different types of customers, this paper proposes an elastic cofactor to describe the electricity price response difference for multiple types of customers. The elastic cofactor can be defined as \( \mu_l \), where \( l \) represents different customer types, then the customer response model considering the elastic cofactor can be expressed by:

\[
\begin{bmatrix}
\Delta Q_m \\
\Delta Q_f \\
\Delta Q_v
\end{bmatrix} = \mu_l E \begin{bmatrix}
\Delta p_p \\
\Delta p_f \\
\Delta p_v
\end{bmatrix}
\]  

(5)

### 2.2 Proportional apportioning technique for hourly load

The electricity price elasticity matrix can be used to obtain the electricity energy of each period after carrying out the TOU. According to the electrical energy of each period after TOU, this paper uses a proportional apportioning technique to calculate the hourly load of each period after TOU [11] by:

\[
P_t' = p_t \left(1 + \frac{\Delta Q_m}{Q_m}\right)
\]  

(6)

where \( P_t' \) and \( P_t \) represent the \( t \)-hour load before and after TOU, respectively.

### 3 | TOU PRICE OPTIMIZATION METHOD CONSIDERING THE BIDIRECTIONAL FEEDBACK EFFECT

Due to the lack of consideration of the bidirectional feedback effect, the traditional TOU optimization results may not reach the global optimum. Therefore, this paper proposes the electricity price-based demand response optimization method with the consideration of the bidirectional feedback effect.

#### 3.1 Period partition based on a moving boundary technique

The period partition algorithm based on a boundary moving technique was first proposed in the paper [11]. Assume that the typical daily load sequence is \( P = \{P_1, P_2, \ldots, P_8, P_9, \ldots, P_{24}\} \), where \( t \) represents hour. Sorting it in ascending order to obtain a new load sequence \( P_o = \{P_{o1}, P_{o2}, \ldots, P_{o8}, P_{o9}, \ldots, P_{o24}\} \). \( S_f \) and \( S_v \) are defined as the valley-flat period’s boundary variable and the flat-peak period’s boundary variable respectively, where \( S_f \) belongs to the valley period and \( S_v \) belongs to the flat period, and \( S_f < S_v \). The iteration scopes of boundary variables are: for \( S_f \): \( P_{o1} \rightarrow P_{o22} \); for \( S_v \): \( P_{o9} \rightarrow P_{o23} \). Determining different period partition results through moving the two boundary variables, taking the minimum mean square distance \( F(S_f, S_v) \) of typical daily load as the objective function, it can be given by:

\[
\min \left\{ F(S_f, S_v) = \frac{1}{24} \sum_{t \in \{1, 2, \ldots, 24\}} (P_t - \bar{P}_t)^2 \right\}
\]  

(7)

where \( \bar{P}_t \) is the cluster centre of the load sequence for the \( m \)-th period, it can be obtained by:

\[
\bar{P}_t = \frac{1}{N_m} \sum_{t \in \{1, 2, \ldots, 24\}} P_t
\]  

(8)

where \( N_m \) is the number of loads during the \( m \)-th period.

### 4 | TOU PRICING OPTIMIZATION MODEL FOR PEAK-VALLEY PERIODS

Generally, the purpose of TOU pricing optimization is to realize the peak shaving and valley filling, which can be achieved by taking the minimum peak load and peak valley difference as the
objective functions [10]. Considering the normalization problem of the objective function, this paper takes the peak load and the peak-valley load difference before TOU as the reference values to normalize the objective function. It can be given by:

\[
    f_1 = \min \left\{ \frac{P'_{\max}}{P_{\max}} \right\} \quad (9)
\]

\[
    f_2 = \min \left\{ \frac{P'_{\max} - P'_{\min}}{P_{\max} - P_{\min}} \right\} \quad (10)
\]

where \(P_{\max}\) and \(P'_{\max}\) represent the peak load of the typical day before and after TOU; \(P_{\min}\) and \(P'_{\min}\) represent the valley load of the typical day before and after TOU; \(f_1\) is the minimized peak load and \(f_2\) is the minimized peak-valley load difference.

4.1 Customer's comprehensive satisfaction model

This paper not merely achieves the peak shaving and valley filling but also considers the optimization of customer's satisfaction after TOU. Customer’s satisfaction [15] can usually be divided into the customer's electricity utilization way satisfaction (EUST) and the customer's electricity charge satisfaction (ECST). Considering comprehensive satisfaction considering

4.1.1 Customer’s electricity utilization way satisfaction

For the flat pricing strategy duration, customer consume electricity in their most comfortable way due to the fixed price throughout the day, while after the implementation of TOU price, the customer will respond the TOU and change their habits of electricity consumption due to different electricity prices of each period, which will cause the change of customer’s EUST. Therefore, customer’s EUST index (SAD1) can be obtained according to the hourly electricity energy before and after TOU, that is:

\[
    SAD_1 = 1 - \frac{\sum_{t=1}^{24} |Q'_t - Q_t|}{\sum_{t=1}^{24} Q_t} \quad (11)
\]

where \(Q_t\) and \(Q'_t\) are the electricity energy in the \(t\)-th period before and after TOU, respectively.

4.1.2 Customer’s electricity charge satisfaction

The electricity charge after TOU is one of the important indices for customers to evaluate the current TOU strategy. Considering the fluctuation of electricity charge caused by the change of power consumption, the customer’s ECST index (SAD2) is generally calculated based on one day’s electricity bill, it can be given by:

\[
    SAD_2 = 1 - \frac{\sum_{m=(p,f,v)} C'_m - C_m}{\sum_{m=(p,f,v)} C_m} \quad (12)
\]

where \(C_m\) and \(C'_m\) are the electricity charge in the \(m\)-th period before and after TOU, respectively.

As mentioned above, the customer’s comprehensive satisfaction index (SAD) can be obtained from the EUST and the ECST by using weight coefficients:

\[
    SAD = \phi_1 \times SAD_1 + \phi_2 \times SAD_2 \quad (13)
\]

Where \(\phi_1\) and \(\phi_2\) are weight coefficients of customer’s EUST and ECST, and \(\phi_1 + \phi_2 = 1\).

Therefore, the customer’s comprehensive satisfaction can be obtained by modifying weight coefficients according to the customer’s recognition degree on the electricity utilization way and the electricity charge.

4.2 Comprehensive satisfaction considering load proportion coefficient

The traditional TOU optimization process only considers the satisfaction of a single type of customer, but for a region, it cannot represent all customer’s types. Therefore, this paper proposes a new customer’s comprehensive satisfaction model by incorporating the load proportion coefficient. The types of load can usually be divided by: the residential load, the commercial load, and the industrial load. Due to the different recognition degree, their corresponding weight coefficients of satisfaction degree are also different. Define the load proportion coefficient to describe different types of customers in a region:

\[
    v_{rl} + v_{cm} + v_{im} = 1 \quad (14)
\]

where \(v_{rl}, v_{cm}\), and \(v_{im}\) represent the load proportion coefficient of the residential load, the commercial load, and the industrial load, respectively.

Therefore, the customer’s comprehensive satisfaction can be reconstructed as:

\[
    SAD_p = \sum_{l=r,c,m} v_l (\phi_{1l} SAD_{1l} + \phi_{2l} SAD_{2l}) \quad (15)
\]

where \(l\) represents different types of customers; \(v_l\) represents the load proportion coefficient of \(l\)-th type; \(\phi_{1l}\) and \(\phi_{2l}\) represent weight coefficients of EUST and ECST of \(l\)-th type load.

4.3 TOU pricing optimization model considering comprehensive satisfaction

The objective function of TOU pricing optimization problem corresponding to the customer’s comprehensive satisfaction can
be summarized as:

\[ f'_3 = \max \{ SAD_p \} \]  

(16)

Considering that \( f_1, f_2, \) and \( f'_3 \) are different optimization types, therefore, this paper transforms \( f'_3 \) into the reciprocal of minimizing customer’s comprehensive satisfaction, namely:

\[ f_3 = \min \left\{ \frac{1}{SAD_p} \right\} \]  

(17)

The objective function of electricity pricing optimization in this paper can be expressed by using the weight coefficient by:

\[ f = \min \left\{ \alpha \frac{P'_{\text{max}}}{P_{\text{max}}} + \beta \frac{P'_{\text{max}} - P'_{\text{min}}}{P_{\text{max}} - P_{\text{min}}} + \gamma \frac{1}{SAD_p} \right\} \]  

(18)

where \( \alpha, \beta, \) and \( \gamma \) represent weight coefficients. This paper uses \textit{fmincon} function of the MATLAB toolbox \[22\] to optimize the above objective function.

4.4 Constraints for TOU pricing optimization

Constraints of TOU pricing optimization including the basic constraints of power system and electricity market, which mainly include income of electricity company, charge of customer, and mutual constraints between prices of different periods.

4.4.1 Income of the electricity company

After TOU, the income of electricity bill for the electricity company will decline due to the other benefits from the TOU strategy, and it can be described by using the benefit coefficient \( \delta \), namely:

\[ \sum_{m=(p,f,v)} C'_m - (1 - \delta) \sum_{m=(p,f,v)} C_m \geq 0 \]  

(19)

4.4.2 Charge of electricity customer

The electricity charge of customer will not increase due to the change in the electricity price after TOU, namely:

\[ \sum_{m=(p,f,v)} C_{ie} - \sum_{m=(p,f,v)} C'_m \geq 0 \]  

(20)

4.4.3 Electricity prices for different periods

In order to realize the peak shaving and valley filling, the electricity price during the peak period should not be lower than that of flat period, and the electricity price during the flat period should not be lower than that of valley period, namely:

\[ p_p - p_f \geq 0 \]  

(21)

\[ p_f - p_v \geq 0 \]  

(22)

where \( p_p, p_f, \) and \( p_v \) represent electricity prices in the peak period, flat, and valley periods, respectively.

4.4.4 Peak-valley price ratio

The peak-valley price ratio constraint has considered to avoid the load inversion between peak-valley periods caused by high peak-valley price difference:

\[ 2 \leq \frac{p_p}{p_v} \leq 5 \]  

(23)

4.4.5 Marginal price

The electricity price during valley period should not be lower than the cost price \( p_d \), namely:

\[ p_v - p_d \geq 0 \]  

(24)

4.5 Electricity price-based demand response optimization method considering the bidirectional feedback effect

This paper presents an electricity price-based demand response optimization method considering the bidirectional feedback effect. That is, result of period partition optimization is used as the input data of TOU pricing optimization, and result of TOU pricing optimization is also back-fed to the period partition optimization.

The TOU pricing optimization is implemented for each moving boundary variable in the period partition optimization process. The value of the objective function after the TOU price optimization is denoted as \( F_{\text{TOU}}(p_p, p_f, p_v) \), and the number of movements of boundary variables is denoted as \( k \). Setting optimal TOU prices for each movement of boundary variables as the objective function of period partition optimization, the expression is shown in:

\[ F_{pp} = \text{best} \left\{ F_{\text{TOU}}(S_{fp}, S_{fp}) \right\} \]  

(25)

Where \( F_{\text{TOU}}(S_{fp}, S_{fp}) \) is a set of recorded objective function values of TOU pricing optimization for each movement of boundary variables, that is \( F_{\text{TOU}} = \{ f \} \), the element is calculated by Equation (18); \( F_{pp} \) is the objective function of the period partition optimization.
The TOU pricing optimization can be regarded as an inner-layer optimization process and the period partition optimization is regarded as an outer-layer optimization process. The flow chart is illustrated in Figure 2. The optimization steps are shown in detail as follows:

**Step1:** Input data. Input the typical daily load sequence $P = \{P_1, P_2, \ldots, P_n, \ldots, P_{24}\}$, and set the iteration number of boundary moving variable $k = 0$.

**Step2:** The new load sequence $P_a = \{P_{a,1}, P_{a,2}, \ldots, P_{a,24}\}$ is obtained by ascending order of current boundary variables:

$\{S_{af}, S_{fb}\}$.

**Step3:** Initialize the boundary variables $S_{af} = P_{a}$, $S_{fb} = P_{a,24}$, where $a = 1, b = 2$.

**Step4:** Initialize the global optimal objective function value $F_{TOU}(p_f, p_v, p_p)$, the global optimal electricity price sequence $p_{best} = \{p_f^*, p_v^*, p_p^*\}$, and global optimal boundary variables $S_{af} = P_{a}$, $S_{fb} = P_{a,24}$.

**Step5:** Update the valley-flat boundary variable. Let $k = k+1$ and $a = a+1$, and if $a < b$, then go to Step 7, otherwise go to Step 6.

**Step6:** Update the flat-peak boundary variable. Let $k = k+1$, $b = b+1$, and $a = 1$, if $b > 23$, then go to Step 8, otherwise go to Step 7.

**Step7:** Update the global optimal variables. Obtain divided periods according to current boundary variables and implement the TOU pricing optimization under the boundary variables. The obtained objective function value is denoted as $F_{best-TOU}(p_f^*, p_v^*, p_p^*)$, if $F_{best-TOU}(p_f^*, p_v^*, p_p^*)$ is better than $F_{best-TOU}(p_f^*, p_v^*, p_p^*)$, then let $F_{best-TOU}(p_f^*, p_v^*, p_p^*) = F_{best-TOU}(p_f^*, p_v^*, p_p^*)$, and update the global optimal electricity price sequence $p_{best} = \{p_f^*, p_v^*, p_p^*\}$.

**Step8:** Output result. Output the global optimal boundary parameters, global optimal electricity price sequence and global optimal objective function value.

### TABLE 1 The optimal boundary variables for April

| Variables | Traditional method | Proposed method |
|-----------|-------------------|-----------------|
| $S_{af}$  | 90.98 MW          | 89.74 MW        |
| $S_{fb}$  | 116.09 MW         | 90.98 MW        |

### TABLE 2 The optimal boundary variables for August

| Variables | Traditional method | Proposed method |
|-----------|-------------------|-----------------|
| $S_{af}$  | 90.84 MW          | 90.81 MW        |
| $S_{fb}$  | 116.45 MW         | 90.84 MW        |

### 5 CASE STUDY

This paper adopts the load data given by the RBTS test system [24], [25]. The peak load is 185 MW, and one month is assumed as the cycle of TOU strategy. The typical daily load of one month is obtained by weighted mean of the daily load of this entire month. For comparing and describing clearly below, the demand response optimization method with the one-way information transmission is called the traditional method (i.e. MTOU), and that with the bidirectional feedback effect (i.e. FTOU) is called the proposed method.

### 5.1 Analysis of period partition result

In this section, the objective function is composed of $f_1$ and $f_2$. In the weight coefficients of objective function are $\alpha = 0.5$, $\beta = 0.5$ ($\gamma$ will be analysed in Part F); the benefit coefficient $\delta = 0.062$; the self-elasticity and cross-elasticity coefficients used in this paper can be found in [11]. The period partition of the typical daily load is implemented by the traditional method and the proposed method, respectively. The optimal boundary variables are shown in Table 1 for April, Table 2 for August, and Table 3 for December. Due to the limited space, this paper only shows the data of April, August and December.
TABLE 3 The optimal boundary variables December

| Variables | Traditional method | Proposed method |
|-----------|--------------------|-----------------|
| $S_{\text{best f}}$ | 109.06 MW | 116.03 MW |
| $S_{\text{best p}}$ | 134.09 MW | 119.27 MW |

Figure 3 Values of objective functions after MTOU and FTOU: (a) for April; (b) for August; (c) for December

Taking April as an example, the global optimal boundary variables based on the traditional method are $S_{\text{best f}} = 90.98$ MW and $S_{\text{best p}} = 116.09$ MW, and the global optimal boundary variables based on the proposed method are $S_{\text{best f}} = 89.74$ MW and $S_{\text{best p}} = 90.98$ MW. This shows that there is a difference between period partition results of the two methods. Therefore, it is necessary to consider the effectiveness of the proposed algorithm in terms of objective function and reliability. Table 2 and Table 3 have the same conclusions.

5.2 Objective function value based on the two methods

Using period partition results of the traditional method and the proposed method to optimize the TOU price, respectively, the obtained objective function values are shown in Figure 3. In addition, the load factor has also been calculated as the research index, which was normalized by the value of factor before TOU [26]. In the figure, $LF$ represents the value of load factor, $PL$ represents the peak load, $PVD$ represents the peak valley difference, $TV/OF$ represents the value of total objective function, MTOU denotes the objective function value obtained by the traditional method, and FTOU denotes the objective function value obtained by the proposed method.

Figure 3 shows that: (1) The load rate has decreased after the implementation of TOU strategy, which indicates that the strategy can reduce the load fluctuation. In addition, the peak load and peak valley difference are both lower than before TOU, which indicates that the implementation of TOU strategy can reduce the load fluctuation and achieve the peak-shaving and valley-filling; (2) compared to the traditional method (i.e. MTOU), the peak load, peak valley difference and total objective function value obtained by the proposed method (i.e. FTOU) has decreased. In April, for example, the peak load drops from 0.595 to 0.454, the peak valley difference from 0.918 to 0.820, and the total objective function value descends to 0.637 from 0.756. Therefore, the proposed method in this paper can further reduce the load fluctuation and improve the objective function value of TOU price optimization. In other words, the proposed method in this paper has a more optimum.

5.3 Comparative analysis of reliability indices

In this paper, the electricity price-based demand response optimization for each month is carried out based on the traditional method and the proposed method, respectively. Taking one year as the calculation cycle and adopting the state enumeration method to complete the reliability assessment, select $LOLP$ (loss of load probability), $LOLE$ (loss of load expectation) and $EENS$ (expected energy not supplied) as reliability indices [27].

\[
LOLP = \sum_{i \in Z} H_i \quad (26)
\]

\[
LOLE = \sum_{i \in Z} H_i T \quad (27)
\]

\[
EENS = \sum_{i \in Z} H_i T (P_i - P_G) \quad (28)
\]

where $H_i$ is the probability of state $i$, $Z$ is the set of system states that cannot meet the load demand within a given time interval (one year in this paper); $T$ is the given time interval; $P_G$ is the total generator’s power at state $i$.

The system reliability indices and percentage histogram corresponding to the two methods are shown in Table 4 and Figure 4.

Table 4 Reliability of power system after the two Methods

| Types       | LOLP   | LOLE   | EENS   |
|-------------|--------|--------|--------|
| Before TOU  | 1.25E-04 | 1.0933 | 9.8675 |
| After MTOU  | 1.47E-05 | 0.1290 | 1.0623 |
| After FTOU  | 5.37E-06 | 0.0471 | 0.3728 |

According to the Table 4: (1) Compared with the initial reliability data without carrying out the TOU strategy, $LOLP$, $LOLE$ and $EENS$ have all decreased after implementing the traditional method (i.e. MTOU) and the proposed method (i.e. FTOU). Taking $EENS$ as an example, before TOU, $EENS$ is 9.8675 MW. When carrying out MTOU and FTOU, $EENS$ have decreased to 1.0623 and 0.3728 MW, respectively. Result for Figure 4 have shown the same conclusion. Therefore, the
The application of TOU strategy can decline the system reliability indices and improve the reliability of the power system. (2) Compared with MTOU, the reliability indices of power system decrease after FTOU. Taking $EENS$ as an example, after using MTOU and FTOU, $EENS$ has decreased from 1.0623 to 0.3728 MW, with a decrease of 0.6895 MW. Result for Figure 4 have shown the same conclusion. Therefore, the proposed method in this paper can further improve the power system reliability compared with the MTOU.

### 5.4 Analysis of TOU pricing optimization

The typical daily load curves after TOU are shown in Figure 5, and the results of TOU pricing optimization are listed in Tables 5–7.

It can be observed from Tables 5–7 that: (1) Comparing with the original price strategy, the peak period price has increased, and the valley period price has decreased after MTOU or FTOU. According to Figure 3, under the effect of elastic matrix, the electricity price difference will lead to the change of consumed electricity energy in different periods; (2) Comparing with MTOU, the peak period price has increased and the flat period price has decreased in the FTOU. Therefore, the FTOU can further reduce the peak period load and increase the flat period load. The same results can also be found in Figure 5.

### 5.5 Impact analysis of the elastic cofactor

In this paper, the customer satisfaction and the load curve are calculated under different elastic cofactors. The FTOU is also used for the electricity price optimization, and the results are illustrated in Figures 6–7.

It can be observed from Figure 6 that: With the increase of the elastic cofactor $\mu$ from 0 to 2, $SAD_1$ decreases gradually, and $SAD_2$ gradually increases first and then reach the saturation state. Therefore, it can conclude that the elastic cofactor can change the customer’s satisfaction which has a negative correlation with $SAD_1$ and has a positive correlation with $SAD_2$. The residential customer, the commercial customer, and the industrial customers are taken as examples: For the commercial customer, the satisfaction index decreases first and then reaches the saturation state, while for the industrial customer, the satisfaction index increases gradually.

### Table 5

| Periods | Before TOU | MTOU | FTOU |
|---------|------------|------|------|
| Peak    | 0.650      | 0.830| 0.911|
| Flat    | 0.650      | 0.723| 0.350|
| Valley  | 0.650      | 0.350| 0.350|

### Table 6

| Periods | Before TOU | MTOU | FTOU |
|---------|------------|------|------|
| Peak    | 0.650      | 0.836| 0.910|
| Flat    | 0.650      | 0.717| 0.350|
| Valley  | 0.650      | 0.350| 0.350|

### Table 7

| Periods | Before TOU | MTOU | FTOU |
|---------|------------|------|------|
| Peak    | 0.650      | 0.836| 0.910|
| Flat    | 0.650      | 0.546| 0.350|
| Valley  | 0.650      | 0.350| 0.350|
customer, customers prefer to consider $\mathcal{SAD}_1$, the elastic cofactor should be lower; for the industrial customer, customers prefer to consider $\mathcal{SAD}_2$, the elastic cofactor should be higher; and for the residential customer, customers have to consider both $\mathcal{SAD}_1$ and $\mathcal{SAD}_2$, the elastic cofactor should be moderate.

With the increase of the parameter $\mu$ from 0 to 2, it can be seen from Figure 7 that the load during peak period has decreased and the load during valley period has increased after the implementation of TOU price. And the difference of load curves with and without consideration of FTOU gradually increased. Therefore, it can conclude that the increase of the elastic cofactor can reduce the fluctuation of the load curve, while the difference between the load curve with FTOU and the original curve without FTOU will be enlarged.

5.6 Analysis of comprehensive satisfaction considering the load proportion coefficient

Since the traditional SAD model only considers the single type of customer, this paper proposes a SAD model which considering the load proportion coefficient. Load curves of the residential customer, commercial customer and industrial customer are obtained by Ref. [28], and weight coefficients of $\mathcal{SAD}_1$ and $\mathcal{SAD}_2$ for three types customers are $\phi_{r1} = 0.5$, $\phi_{r2} = 0.5$; $\phi_{c1} = 0.9$, $\phi_{c2} = 0.1$; $\phi_{i1} = 0.2$, $\phi_{i2} = 0.8$, respectively. The elastic cofactors proposed in this paper are used to consider the response diversity for different types of customers, and the elastic cofactor $\mu$ for three types of customers are $\mu_r = 1$, $\mu_c = 0.5$, $\mu_i = 1.5$, respectively. The FTOU strategy is adopted to complete the demand response optimization.

In this section, three cases (Case I, Case II and Case III) are designed under different load proportion coefficients for analysing the effectiveness of the proposed customer satisfaction model, and weight coefficients of the objective functions (WC) are fixed as: $\alpha = 0.1$, $\beta = 0.1$, $\gamma = 0.8$, respectively. Load proportion coefficients for Case I: $\nu_r = 0.2$, $\nu_c = 0.2$, $\nu_i = 0.6$; for Case II: $\nu_r = 0.2$, $\nu_c = 0.6$, $\nu_i = 0.2$; for Case III: $\nu_r = 0.6$, $\nu_c = 0.2$, $\nu_i = 0.2$. The FTOU model considering $\mathcal{SAD}$ of the single type customer and the proposed $\mathcal{SAD}_{P}$ model are optimized, respectively, and the results are illustrated in Figure 8.

In Figure 8, $\mathcal{SAD}_{RE}$, $\mathcal{SAD}_{CO}$, $\mathcal{SAD}_{IN}$ denote the SAD model with residential customers, commercial customers, and industrial customers, respectively. $\mathcal{SAD}_{LPC}$ denotes the SAD model with the load proportion coefficients. It can be observed from Figure 8 that: under the objective functions with the same weight coefficients, the FTOU model considering the $\mathcal{SAD}_{LPC}$ can obtain the optimal objective function value for different load proportion coefficients. Taking Case I and Case II as examples, the objective function values obtained by FTOU model considering the $\mathcal{SAD}_{RE}$ are 0.946 and 0.970, respectively; the objective function values obtained by FTOU model considering the $\mathcal{SAD}_{CO}$ are 0.967 and 0.970, respectively; the objective function values obtained by FTOU model considering the $\mathcal{SAD}_{IN}$ are 0.943 and 0.972, respectively; the objective function values obtained by FTOU model considering the $\mathcal{SAD}_{LPC}$ are 0.943 and 0.970, respectively. Therefore, the proposed TOU price model considering $\mathcal{SAD}_{LPC}$ can improve the objective function value of FTOU price for different load proportion coefficients.

In this section, four cases (Case IV, Case V, Case VI and Case VII) are designed for analysing the effectiveness of the
In conclusion, comparing with the traditional method, the proposed method can achieve better results, which has a great significance on reducing load fluctuation, enhancing power system reliability and improving the satisfaction degree of customers.

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REFERENCES

1. Chen, S., Alan Love, H., Liu, C.: Optimal Opt-In Residential Time-of-Use Contract Based on Principal-Agent Theory. IEEE Trans. Power Syst. 31(6), 4415–4426 (2016)
2. Huang, W., Zhang, N., Kang, C., et al.: From demand response to integrated demand response: Review and prospect of research and application. Protection and Control of Modern Power Systems. 4(2), 148–150 (2019)
3. Zhou, B., Yang, R., Li, C., et al.: Multi-objective Model of Time-of-Use and Stepwise Power Tariff for Residential Consumers in Regulated Power Markets. IEEE Syst. J. 12(3), 2676–2687 Sept. (2018)
4. Hu, Y., Li, Y., Chen, L.: Multi-Objective Optimization of Time-of-Use Price for Tertiary Industry Based on Generalized Seasonal Multi-Model Structure. IEEE Access. 7, 89234–89244 (2019)
5. Ming, H., Xia, B., Lee, K.Y, et al.: Prediction and assessment of demand response potential with coupon incentives in highly renewable power systems. Proc. Control of Mod. Power Syst. 5(2), 724–137 (2020)
6. Gunduz, H., Jayaweera, D.: Reliability assessment of a power system with cyber-physical interactive operation of photovoltaic systems. Int. J. Electr. Power Energy Syst. 101, 371–384 (2018)
7. Yang, H., Yang, S., Xu, Y., et al.: Electric vehicle route optimization considering time-of-use electricity price by learnable partheno-genetic algorithm. IEEE Trans. Smart Grid. 6(2), 657–666 (2015)
8. Assolami, Y., Morsi, W.: Impact of second generation plug-in battery electric vehicles on the aging of distribution transformers considering TOU prices. in IEEE Trans. Sustainable Energy. 6(4) 1606–1614 (2016)

9. Hung, Y., Michailidis, G: Modeling and optimization of time-of-use electricity pricing systems. IEEE Trans. Smart Grid. 10(4), 4116–4127 (2019)

10. Yang, H., Wang, L., Zhang, Y., et al.: Reliability evaluation of power system considering time of use electricity pricing. IEEE Trans. Power Syst. 34(3), 1991–2002 (2019)

11. Yang, H., Wang, L., Ma, Y.: Optimal time of use electricity pricing model and its application to electrical distribution system. IEEE Access. 7, 123558–123568 (2019)

12. Yang, P., Tang, G., Nehorai, A.: Optimal time-of-use electricity pricing using game theory. In: 2012 IEEE International Conference on Acoustics, Speech and Signal Processing, Kyoto, pp. 3081–3084 (2012)

13. Yang, P., Tang, G., Nehorai, A.: A game-theoretic approach for optimal time-of-use electricity pricing. IEEE Trans Power Syst. 28(2), 884–892 (2013)

14. Li, D., et al.: Research on optimization of multi energy-type coordinated microgrid considering user satisfaction. In: Proceedings of IEEE Conference on Energy Internet and Energy System Integration, Beijing, pp. 1–6 (2017)

15. Dou, C., Meng, C., Yue, W., et al.: Double-deck optimal schedule of microgrid based on demand-side response. IET Renew. Power Gener. 13(6), 847–855 (2019)

16. Gao, F., et al.: Day-ahead energy optimal scheduling of household microgrid considering the user satisfaction. In: Proceedings of 2015 IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC), Brisbane pp. 1–5 (2015)

17. Kahnamouei, A.S., Bolandi, T.G., Haghifam, M.: The conceptual framework of resilience and its measurement approaches in electrical power systems. In: IET International Conference on Resilience of Transmission and Distribution Networks, Birmingham, U.K., pp. 1–11 (2017)

18. Shanfima, S., Rastegar, M., Allahbakhshi, M., et al.: Inverse reliability evaluation in power distribution systems. IEEE Transactions on Power Systems. 35(1), 818–820 (2020)

19. He, R., Xie, H., Deng, J., et al.: reliability modeling and assessment of cyber space in cyber-physical power systems. IEEE Transactions on smart grid. 11(5), 3763–3773 (2020)

20. Billinton, R., Kumar, S., Chowdhury, N., et al.: A reliability test system for educational purposes-basic data. IEEE Transactions on Power Systems. 4(3), 1238–1244 (1989)

21. de Sa Ferreira, R., Barroso, L. A, Rochinha Lino, P., et al.: Time-of-use tariff design under uncertainty in price-elasticities of electricity demand: A stochastic optimization approach. IEEE Trans. Smart Grid. 4(4), 2285–2295 (2013)

22. Kusakana, K., Optimal scheduled power flow for distributed photovoltaic/wind/diesel generators with battery storage system. IET Renew. Power Gener. 9(8), 916–924 (2015)

23. Safdarian, A., Fotuhi-Firuzabad, M., Lehtonen, M.: A medium-term decision model for DisCos: Forward contracting and TOU pricing. IEEE Trans Power Syst. 30(3), 1143–1154 (2015)

24. Billinton, R., Kumar, S., Chowdhury, N., et al.: A reliability test system for educational purposes-basic data. IEEE Trans. Power Syst. 4(3), 1238–1244 (1989)

25. Subcommittee, P.M.: IEEE reliability test system. IEEE Trans. Power App. Syst. PAS-98(6), 2047–2054 (1979)

26. Nachprayoon, S.: Calculation and allocation of load losses in distribution system using load research data and load factor method. In: 2016 6th IEEE International Conference on Control System, Computing and Engineering (ICCSCE), Batu Ferringhi, pp. 85–90 (2016)

27. Karki, R.: Renewable energy credit driven wind power growth for system reliability. Electric Power Systems Research. 77, 797–803 (2006)

28. Kalesar, B.M.: Customers swapping between phases for loss reduction considering daily load profile model in smart grid. In: Proceedings of CIRED Workshop, Helsinki pp. 1–4 (2016)

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