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An Effective Method of Equivalent Load-Based Time of Use Electricity Pricing to Promote Renewable Energy Consumption

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Abstract: The variability and intermittency inherent in renewable energy sources poses significant challenges to balancing power supply and demand, often leading to wind and solar energy curtailment. To address these challenges, this paper focuses on enhancing Time of Use (TOU) electricity pricing strategies. We propose a novel method based on equivalent load, which leverages typical power grid load and incorporates a responsibility weight for renewable energy consumption. The responsibility weight acts as an equivalent coefficient that accurately reflects renewable energy output, which facilitates the division of time periods and the development of a demand response model. Subsequently, we formulate an optimized TOU electricity pricing model to increase the utilization rate of renewable energy and reduce the peak–valley load difference of the power grid. To solve the TOU pricing optimization model, we employ the Social Network Search (SNS) algorithm, a metaheuristic algorithm simulating users' social network interactions to gain popularity. By incorporating the users' mood when expressing opinions, this algorithm efficiently identifies optimal pricing solutions. Our results demonstrate that the equivalent load-based method not only encourages renewable energy consumption but also reduces power generation costs, stabilizes the power grid load, and benefits power generators, suppliers, and consumers without increasing end users' electricity charges.

Keywords: renewable energy consumption; equivalent load; time of use pricing; demand response

MSC: 90B50

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1. Introduction

In the last decade, there has been a remarkable surge in the deployment of renewable energy, a steady rise in its contribution to electricity generation, and a substantial decline in the cost of electricity production. According to data released by China's National Energy Administration, the installed capacity of renewable energy reached 1.213 billion kilowatts, accounting for 47.3% of the total installed capacity of national power generation by the end of 2022. The capacity of non-fossil fuel power generation has surpassed that of thermal power. In 2021, the guiding prices for newly built wind and photovoltaic power projects in many provinces of China were lower than the benchmark prices for thermal power generation, with the exception of Qinghai and Hainan province. Building a new type of power system dominated by renewable energy has become an inevitable choice.

The increasing integration of renewable energy, particularly wind and photovoltaic power, into the power system, has introduced significant operational challenges due to the unpredictable nature of their output and intermittency [1,2]. This has led to the emergence of wind and photovoltaic power curtailment, underscoring the imperative to enhance power utilization efficiency. Leveraging market incentive mechanisms to mobilize demand-side resources, boost renewable energy consumption, and alleviate operational pressures on the system is imperative [3]. Time of Use (TOU) pricing is a vital market mechanism for demand-side management, playing a crucial role in encouraging users to adjust their power loads, fostering user participation in maintaining power system balance, and increasing renewable energy consumption [4]. Previous studies have explored various aspects of demand response to promote renewable energy consumption [5]. The authors of [6] studied the operating mode of demand response from aspects such as trading and pricing mechanisms, financing, and technical services. The authors of [7] proposed an economic dispatch strategy considering the uncertainty of renewable energy and demand-side response. The authors of [8] established an optimization model for a virtual power plant, considering both reliable response loads and stochastic response loads, providing a means for user-side resources to participate in power dispatch. The authors of [9] used a Time of Use pricing strategy to guide users to participate in demand response, achieve linkage between photovoltaic power generation and thermal power generation, and improve the consumption capacity of photovoltaic power generation.

The context for applying TOU pricing is undergoing new changes: firstly, the proportion of renewable energy with uncertain output on the generation side is increasing, and the power consumption structure on the demand side is changing rapidly, with bidirectional fluctuations in power production and consumption; secondly, after a large amount of renewable energy is connected, the marginal supply costs decrease significantly with the changes in the output structure of the power. In addition, the diversification of power consumption structure and the large-scale application of new energy storage devices in power consumption have increased the demand response capability of users. Therefore, there is an urgent need to enhance the Time of Use (TOU) pricing mechanism [10], taking into full account the power structure on the generation side, accurately reflecting electricity costs, and avoiding price distortions. By forming effective market-oriented TOU pricing signals, this approach aims to motivate and encourage users to optimize their power usage, engage in peak shaving, improve the power supply–demand balance, and foster the development of green and low-carbon energy solutions.

From a demand response perspective, this paper designs a TOU pricing mechanism based on equivalent load, taking into account renewable energy consumption and generation costs, to facilitate the transition of the new power system from "source following load changes" to "source–load interaction". Firstly, a method for computing equivalent load is proposed based on the typical load of the power grid. By introducing the responsibility weight of renewable energy power consumption as the equivalent coefficient, an equivalent load curve reflecting the power source structure is generated. Secondly, a demand response model is constructed to eliminate the influence of natural trends, avoiding overestimating the degree of user response to electricity prices. Finally, with the lowest cost on the power source side as the optimization goal, and increasing the utilization rate of renewable energy and reducing the peak–valley difference of the power grid load as constraints, a Time of Use pricing optimization model is designed. The TOU pricing model is solved using a metaheuristic algorithm known as the Social Network Search (SNS) algorithm. By incorporating four innovative optimization operators (moods): Imitation, Conversation, Disputation, and Innovation, the SNS algorithm efficiently identifies optimal pricing solutions through expressed opinions. The method proposed in this paper not only encourages the uptake of renewable energy but also achieves a reduction in generation costs without increasing electricity expenses for users. Moreover, it contributes to the stabilization of power grid loads, leading to a mutually beneficial outcome for all stakeholders within the power system. Figure 1 serves as a comprehensive structural diagram that delineates the organization of this paper.

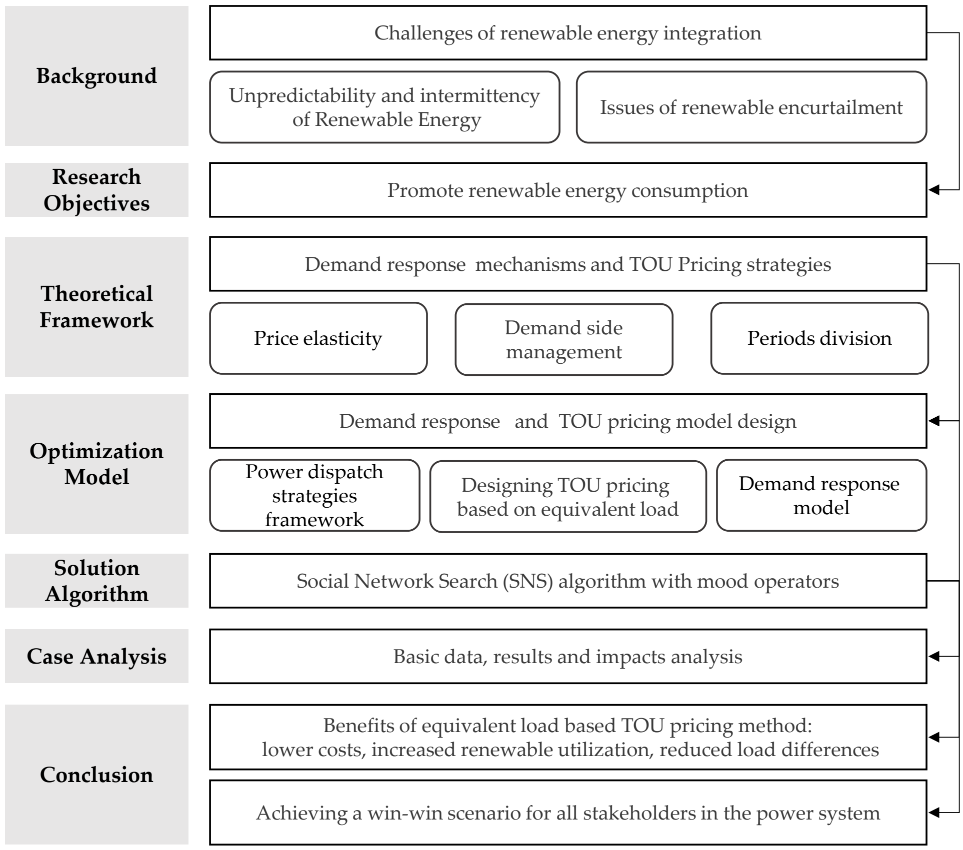


Figure 1. Structural diagram of Equivalent Load-based TOU Pricing optimization.

2. Time of Use Pricing Mechanism

Traditional Time of Use pricing is mainly designed based on the typical load curve of the power supply side. According to the typical load, the day is divided into peak, flat, and valley periods, with higher electricity prices during peak hours and lower electricity prices during off-peak and valley hours. Some provinces also set sharp prices, seasonal prices, or peak–load and off-peak–load prices. Through differentiated pricing, the pricing signals are fully utilized to instruct users to reduce electricity consumption as much as possible during peak hours and increase electricity usage during off-peak hours, achieving the goals of peak shaving, filling valleys, alleviating the imbalance between power supply and demand, and ensuring the security of the power system.

While electricity is homogeneous for users, there is a significant difference in the marginal generation cost of different energy types on the generation side. Compared to conventional thermal power, renewable energy has significantly reduced marginal generation costs due to the expansion of installed capacity and technological progress. Designing Time of Use pricing solely based on the typical load on the supply side poses challenges in effectively conveying the power source structure and cost information to the demand side. This could result in cost inversion, where users consume inexpensive electricity but pay higher prices. Figure 2 illustrates the multi-source output curve of a certain region's power generation side, showing higher total output from 10 a.m. to 12 p.m. During this period, if Time of Use pricing is designed based solely on the typical load, increasing electricity prices may not be conducive to the consumption of photovoltaic power, which peaks during these hours.

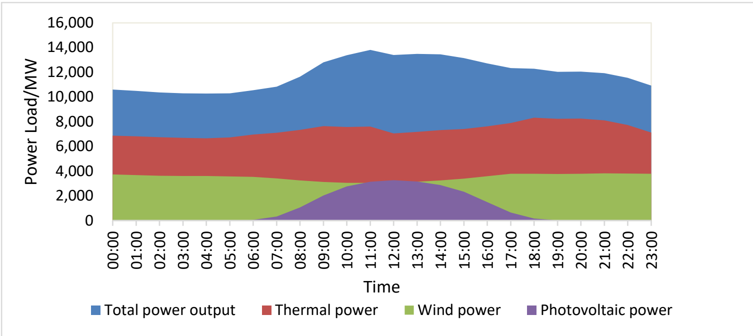


Figure 2. Energy output curve at power generation side.

Therefore, it is necessary to optimize the traditional Time of Use pricing design method based on the typical load of the power grid, taking into account factors such as the consumption of renewable energy and generation-side costs. In fact, since the issuance of the "Notice on Further Improving the Time of Use Pricing Mechanism" (Development and Reform Price [2021] No. 1093), various regions have continuously optimized Time of Use pricing policies based on specific circumstances and reasonably divided time periods. Nationwide, the period from 23:00 to 7:00 is mostly set as the valley period at night; however, in many provinces (regions), valley prices are implemented during midday when renewable energy output is relatively high. Shandong province has even divided 2–3 h of deep valley periods based on seasons. Time of Use pricing design should take into account the energy structure on the generation side.

2.1. Equivalent Load Considering Renewable Energy Consumption

Due to the volatility and intermittency of renewable energy output, its uncertainty over time, and its uneven distribution in space, significant challenges are posed to the balance of electrical power and the safe and reliable operation of a new power system. Optimizing the design of a Time of Use pricing mechanism to guide users to consume more electricity during peak periods of renewable energy output, and transforming the power balance mode from power generation tracking load to source-load interaction, are crucial for enhancing renewable energy consumption, promoting structural reforms on the power supply side, and driving the high-quality development of electric power.

Time of Use (TOU) pricing is primarily developed based on the power grid load curve and focuses on optimizing various types of loads such as typical load, baseline load, quasi-load, net load, and equivalent load. The typical load refers to the average or expected electricity load on the grid under normal conditions. The baseline load is the amount of electricity that would have been consumed without any interventions. Quasi-load is defined by the ideal load shape that the system aims to achieve. Net load represents the actual electricity load on the grid after subtracting the generation from renewable sources like solar and wind. The equivalent load proposed in this paper is a theoretical load, composed by considering the contribution and variability of renewable energy sources. In reference [11], a TOU pricing optimization model uses a BP neural network and grey prediction method to forecast the typical load curve, taking into account factors like load development and user behavior. Reference [12] discusses demand response by classifying it into two types: baseline and quasi-load. The baseline type assesses user contributions by assuming a baseline value for times when they do not participate in demand response, using methods such as averaging or regression of load data. Although adjustment factors are introduced to enhance prediction accuracy, establishing a reliable baseline remains a challenge, particularly in gaining user acceptance. The quasi-load type evaluates user contributions based on the ideal load shape provided by the system, as noted in references [13,14]. This load is determined by the demand response center based on overall network operation parameters, aiming to minimize operating costs and enhance renewable energy consumption. However, this model does not account for the impact of uncertainty factors and fails to capture the benefits of complementary user load. Despite proposals for dynamic self-organizing aggregation solutions, their practical application remains complex.

Many scholars base their Time of Use pricing designs on net load [15–17], which directly corresponds to the high-cost non-renewable energy output. In reference [15], an autoregressive moving average method is used for wind speed simulation, and a segmented function relationship between wind power output and wind speed is determined using historical data. The wind power output is then obtained, and the system's net load, with the goal of minimizing the peak–valley difference in the expected value of net load generated by conventional units after complete wind power consumption, is used as the target function for Time of Use pricing model optimization. However, this method assumes "complete wind power consumption" as a prerequisite in the optimization objective, which does not fully align with reality, and it does not indicate how the design of a Time of Use pricing mechanism can promote consumption. Reference [16] refers to the net load curve obtained by subtracting wind and photovoltaic power generation output from the grid load curve as the equivalent load curve. Equivalent load is used as the optimization target for Time of Use pricing, dividing the equivalent load curve into periods using fuzzy membership functions. It suggests that implementing new Time of Use pricing will encourage consumers to change their electricity usage habits and amounts, leading to a decrease in user comfort. The paper introduces two main concepts, "load transfer rate" and "user comfort", considering consumer psychology. It transforms the optimization objectives of minimizing peak–valley differences and maximizing user comfort into a single objective through linear weighting conversion, and uses a genetic algorithm for optimization, but it does not provide principles and methods for determining weighting factors, nor does it compare the improvement in renewable energy consumption before and after optimization. Reference [17] models peak–valley Time of Use pricing optimization based on the contributions of load and new energy output to the "duck curve" membership degree during different periods. This method aims to maximize renewable energy consumption under the constraint that the total electricity cost change before and after optimization is between 0–1%, but it does not consider the impact on the peak–valley load difference in the power grid and generation-side costs.

The limitation of the net load method is that the net load is only a part of the grid supply load, making it unsuitable for period division based on the net load. Moreover, the improvement in the peak–valley difference of the net load does not necessarily indicate a better effect on promoting renewable energy consumption. Considering the advantages and limitations of various load curves, this paper designs an equivalent load indicator, provides its computation method, and conducts Time of Use pricing optimization based on the equivalent load.

2.1.1. Definition and Computation of Equivalent Load

The term "equivalent" refers to a comprehensive indicator or value equivalent to a specific numerical value, such as the "pollution equivalent" measuring different pollutants' environmental impact, or the "equivalent electricity price" considering integrated capacity costs and electricity costs. Drawing on the basic idea of "equivalence", the load indicator considering renewable energy consumption and transformed through computation is defined as the "equivalent load". Unlike the power grid's typical load, the equivalent load is computed by considering various factors that influence the demand and supply dynamics of the power grid, particularly focusing on the contribution and variability of renewable energy sources. By introducing the responsibility weight of renewable energy consumption as the equivalent coefficient and basing it on the typical load, the equivalent load is adjusted according to the proportion of renewable energy in the total energy mix, effectively weighting the renewable energy output more heavily when it is available in abundance and less during scarcity. The total electricity corresponding to the equivalent load curve and the typical load curve is the same; hence, it is called "equivalent load". The equivalent load curve is significant because it provides a more accurate representation of the actual load on the grid that accounts for renewable energy fluctuations. By doing so, it allows for a TOU pricing strategy that not only responds to traditional demand patterns but also aligns closely with the availability of renewable energy, encouraging a more efficient and sustainable energy usage pattern.

The computation method of equivalent load is as follows:

Step One: Standardize the typical load on the supply side using the Min–Max normalization method, mapping the load data to a value between [0, 1], making it dimensionless and comparable across different scales or units:

$$L(t)' = \frac{L(t) - \min(L)}{\max(L) - \min(L)} \tag{1}$$

where $L(t)'$ is the standardized typical power grid load at time t; L is the typical power grid load, $L(t)$ is the power grid load at time t, and max(L) and min(L) are the maximum and minimum values of the typical power grid load.

Step Two: Standardize the renewable energy output on the generation side using the Max–Min method to [0, 1]:

$$L_r(t)' = \frac{\max(L_r) - L_r(t)}{\max(L_r) - \min(L_r)} \tag{2}$$

where $L_r(t)'$ is the standardized renewable energy consumption at time t; $L_r(t)$ is the renewable energy consumption at time t, and max(L_r) and min(L_r) are the maximum and minimum values of the renewable energy consumption.

The Max–Min method inversely scales the values, where higher original values are translated into lower normalized values, and vice versa. This inverse scaling is particularly advantageous in a demand-response context, as lower normalized values correspond to periods of high renewable energy production. This alignment encourages increased energy usage during these periods, promoting the consumption of renewable energy when it is most abundant.

Step Three: Combine the two standardized values from steps One and Two using the renewable energy consumption responsibility weight ω with an adjustable coefficient β to obtain the standardized equivalent load:

$$L_e(t)' = (1 - \beta\omega)L(t)' + \beta\omega L_r(t)' \tag{3}$$

where $L_e(t)'$ is the standardized equivalent load at time t, $L_e(t)' \in [0, 1]$; ω is the renewable energy equivalent coefficient; β is the adjustment coefficient.

Step Four: Restore the standardized equivalent load $L_e(t)'$ using Formula (4) to obtain the equivalent load $L_e(t)$ at time t:

$$L_e(t) = \frac{L_e(t)' \times (\sum_t^N \delta(t)L(t) - N\delta(t)\min(L))}{\sum_t^N \delta(t)L_e(t)'} + \min(L) \tag{4}$$

where $L_e(t)$ is the equivalent load at time t, $\delta(t)$ is the unit interval when sampling load data, typically 1 h, so N =24.

The typical load $L(t)$ can be provided by the local power company or computed based on the actual load of the power grid. Computation methods include the maximum daily load method, mean method, weighted average method, fuzzy C-means clustering algorithm, etc. [18]. Some scholars have proposed methods that consider grid load data and fit the typical load based on a normal distribution [19]. These methods are complex, and since determining the typical load is not the focus of this research, this paper simplifies the process by collecting the daily load data and calculating the typical load $L(t)$ using the mean method.

2.1.2. Influences of Parameters

As indicated by Equation (3), the value of the standardized equivalent load $L_e(t)'$ is affected by parameters ω and β. The renewable energy equivalent coefficient ω is directly taken as the renewable energy power consumption responsibility weight value published annually by the national energy regulatory authority. The computation of ω is shown in Equation (5):

$$\omega = \frac{\sum_i^m Q_{ri}}{\sum_j^n Q_j} \tag{5}$$

where $\sum_i^m Q_{ri}$ is the total annual consumption of m kinds of renewable energy, and $\sum_j^n Q_j$ is the total consumption of various power sources.

As renewable energy output is standardized using the Max–Min method, according to Equations (3) and (4), under the same $\beta\omega$, the larger $L_r(t)$ is, the smaller the equivalent load will be. Conversely, the effect is similar to the "duck curve" where more photovoltaic power leads to lower "net load". However, unlike the "duck curve", the equivalent load does not completely deduct renewable energy output. Instead, it uses a relative conversion method determined by $\beta\omega$. Changing the values of β and ω, a larger product of $\beta\omega$ leads to a deeper deviation of the equivalent load curve from the power grid's typical load curve. Conversely, it becomes closer to the original typical load curve.

The equivalent coefficient ω represents the renewable energy power consumption responsibility weight, which indicates the target proportion of renewable energy usage. A higher proportion of renewable energy generation corresponds to a larger ω. Essentially, by tailoring TOU pricing according to the renewable energy power consumption responsibility weight ω, we can directly influence the demand side of electricity consumption based on the energy structure. This adjustment in electricity demand encourages the use of renewable energy, thereby creating a synergy between renewable energy consumption on the generation side and load management on the demand side. This approach facilitates the transition of the power system from a "source following load" model to a "source–load interaction" paradigm, promoting a more dynamic and responsive energy system.

As ω is determined externally and published annually by the national energy regulatory authority, it is not a parameter that can be adjusted internally. When TOU pricing does not match ω, adjustments to the degree to which the equivalent load is affected can be made based on β.

The parameter β is a scaling factor that adjusts the influence of the renewable energy equivalent coefficient ω on the equivalent load calculation. It directly affects how much weight is given to the renewable energy output relative to the typical load in the final equivalent load computation.

By adjusting β, the model can be fine-tuned to optimize both economic and environmental outcomes in the power sector. If β = 0, Equation (3) simplifies to $L_e(t)' = L(t)'$, meaning the equivalent load is entirely based on the typical load, with no influence from renewable energy. If β = 1, Equation (3) becomes $L_e(t)' = (1-\omega)L(t)' + \omega L_r(t)'$, indicating a balanced influence based on the value of ω.

Typically, β is set to 1, but it can be modified based on the specific requirements and objectives of TOU pricing management to better match local conditions and optimize the effectiveness of the pricing strategy. This flexibility in adjusting β provides a mechanism to adapt the model for varying regional energy dynamics and policy goals.

Figure 3 illustrates the equivalent load curves under three specific scenarios: when β = 1 with ω values of 0.16 and 0.32, and when β = 0.5 with ω = 0.16. The dashed line represents the equivalent load, the solid black line represents the grid's typical load curve, and the solid green line represents the actual output curve of renewable energy.

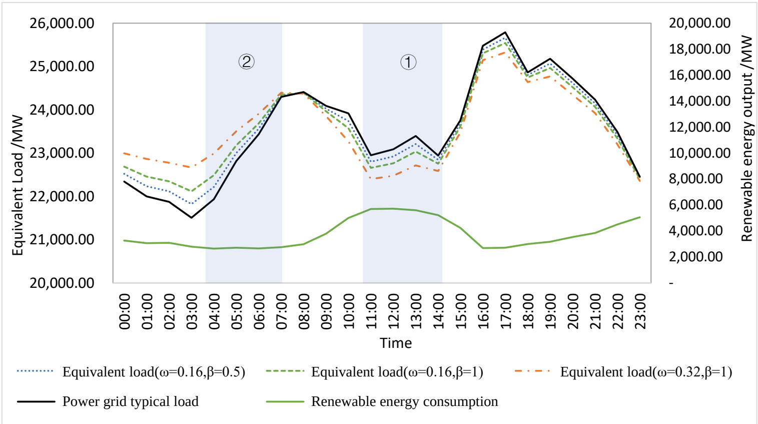


Figure 3. Equivalent load curve and renewable energy consumption curve.

According to Figure 3, during periods of high renewable energy output (such as zone ① from 11 a.m. to 2 p.m.), the equivalent load decreases. Because the equivalent load curve is below the typical load curve, according to demand response and compared to Time of Use pricing based on the typical load curve, the average electricity price in zone ① should be reduced when optimizing Time of Use pricing based on the equivalent load curve, thereby stimulating electricity consumption and increasing user electricity usage during that time period.

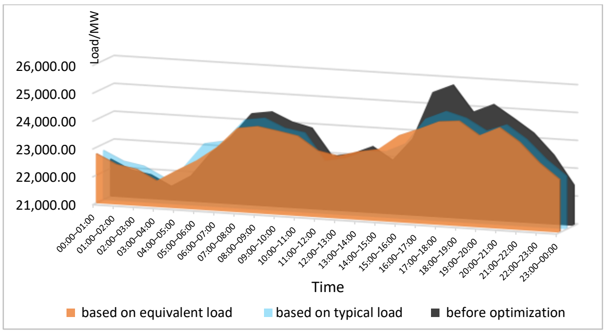
Figure 4 provides a detailed depiction of the impacts on both the load on the supply side and the output on the generation side before and after implementing Time of Use (TOU) pricing optimization based on typical and equivalent load methods.

In Figure 4a, the comparison between the pre-optimized grid's typical load and the post-optimization scenarios reveals that TOU pricing optimization, whether based on typical or equivalent load, effectively reduces the peak-to-valley difference in grid load. Notably, the equivalent load optimization method enhances grid stability more significantly. During the periods marked as zone ①, there is a noticeable increase in grid load, which strategically aligns with high renewable energy output periods, thereby promoting greater consumption of renewable energy.

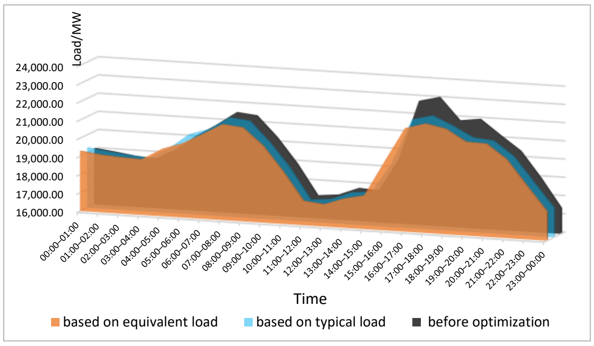
Figure 4b illustrates the impact on non-renewable energy output, showing a flatter output curve post-optimization compared to the pre-optimization curve. This flattening indicates a more consistent and efficient operation of conventional power generation units, which contributes to the economic efficiency of these units by reducing the need for rapid ramping up and down in response to demand fluctuations.

Lastly, Figure 4c compares the effects on renewable energy consumption before and after optimization using both methods. It is evident that the equivalent load method is particularly effective in boosting renewable energy consumption. This method not only aligns demand with renewable energy availability more closely but also facilitates a higher integration of renewable energy into the grid. This is quantitatively reflected in the increased proportion of renewable energy in the total energy mix and a corresponding decrease in reliance on non-renewable sources.

Similarly, during periods of low renewable energy output (such as zone ② from 4 a.m. to 7 a.m.), the equivalent load curve is above the typical load curve. When designing Time of Use pricing based on the equivalent load curve, the average electricity price in zone ② increases compared to the typical load method, which is consistent with the characteristics of low renewable energy output in zone ②.



(**a**)



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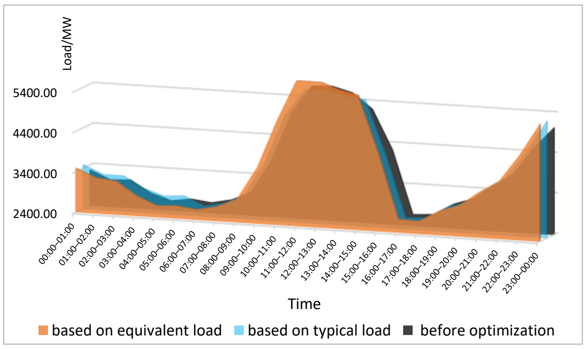

(**c**)

Figure 4. Loading comparison based on equivalent load and typical load. (**a**) power grid load; (**b**) non-renewable energy output; (**c**) renewable energy consumption.

Overall, the quantitative analysis in Figure 4 underscores the effectiveness of TOU pricing optimization, especially when using the equivalent load method, in promoting a more stable and economically efficient grid operation while enhancing the consumption of renewable energy.

2.2. Dispatch Strategies to Promote Renewable Energy Consumption

"Source–load interaction" to promote the consumption of renewable energy also requires corresponding implementation of dispatch strategies [17]. According to the requirements of the National Renewable Energy Law and the Comprehensive Supervision Work Plan for Clean Energy Consumption (National Energy Comprehensive Regulation [2021] No. 28) issued by the National Energy Administration, grid enterprises should prioritize the dispatch and full purchase of renewable energy generation. As weather forecasts become more accurate, wind farms and photovoltaic power stations gradually exhibit characteristics of observable and predictable conventional power sources [20,21].

At the same time, through the optimization of dispatch technology on the supply side, the space for renewable energy consumption can be further explored.

The dispatch strategies framework to promote renewable energy consumption is shown in Figure 5. This framework guides the decision-making process in adjusting energy outputs based on the changes in electricity load after demand response (ΔL) and the availability of renewable energy.

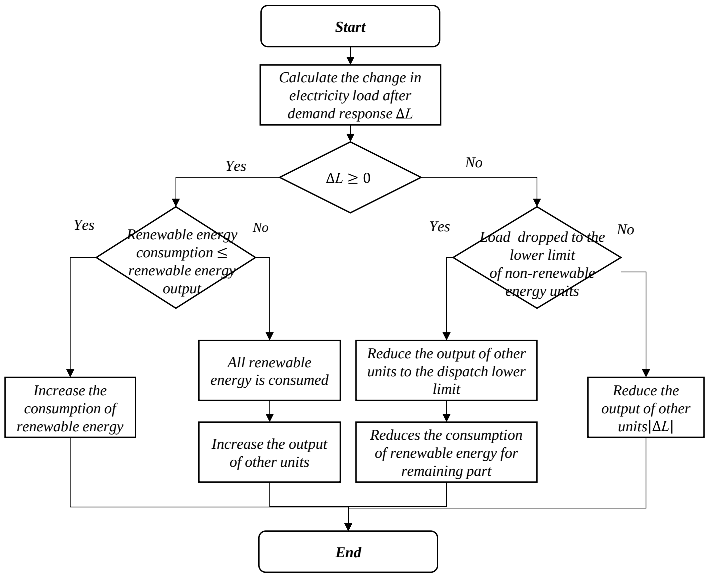

Figure 5. Dispatch strategies for promoting renewable energy consumption.

The framework begins by calculating the change in electricity load after demand response, denoted as ΔL. The decision-making process is as follows:

(1) If ΔL is non-negative, which implies an increase or no change in load:

Check if the renewable energy consumption is within the output limits. If yes, increase ΔL of the consumption of renewable energy. If no, ensure all available renewable energy output is fully utilized, and increase the output of other units to meet the total demand.

(2) If ΔL is negative, indicating a decrease in load:

Check if the load has dropped to the lower limit for non-renewable units. If so, reduce their output to the minimum dispatch limit, and adjust the renewable energy output to match the reduced load to maintain balance. If the load has not dropped to the lower limit, decrease ΔL of the output of other units accordingly.

The dispatch strategies framework provides a structured approach to adjusting power outputs based on changes in load, specifically aiming to maximize the use of renewable energy while maintaining system stability.

3. User Demand Response

Demand response is the market participation behavior of electricity users who respond to market price signals or incentive mechanisms and change their inherent electricity consumption patterns [22]. Demand response can be categorized into market price-based demand response and policy incentive-based demand response [23]. Price-based responses include peak–valley Time of Use pricing, real-time pricing, and others, while incentive-based responses involve interruptible loads, direct load control, emergency electricity demand response, etc. [24]. Time of Use pricing is an important mechanism designed based on the time value of electricity [25]. By setting different price levels for different time periods, Time of Use pricing is made to be closer to the supply cost of the power system. This maximizes the role of price signals, guiding electricity users to use less power during peak hours and more power during off-peak hours, to ensure the safe and stable operation of the power system, enhance overall system efficiency, and reduce the overall societal electricity costs. In this paper, based on user demand response and load curves, different time periods are defined, and different electricity prices are set.

3.1. Division of Periods

The division of peak–valley periods is the foundation for formulating and implementing Time of Use pricing. Peak–valley period division should reflect the actual peak–valley characteristics of the network supply load curve and also demonstrate the differences in electricity costs during different periods. Electricity users pay higher electricity fees for high-cost electricity during high-cost periods like sharp and peak periods and lower fees for low-cost electricity during valley period. This clarifies market signals to guide users to adjust their electricity consumption behavior. The "Notice on Further Improving the Time of Use Pricing Mechanism" proposes a scientific approach to period division, stating "Identify peak hours as periods of tight supply and high marginal supply cost, and off-peak hours as periods of relaxed supply and low marginal supply cost" [10]. Methods for period division typically include clustering based on load characteristics, cost-based methods based on supply cost, and factor analysis methods [26]. Among them, clustering methods evaluate the likelihood of each point on the load curve being in various periods based on the numerical characteristics of the load, using membership or similarity functions to determine sharp, peak, flat, and valley periods. Clustering methods include fuzzy clustering [27], C-means clustering, and SOM neural network clustering [28]. These clustering methods are based on load values and ignore time sequence, making the division of periods too separated and not conducive to users adjusting their electricity consumption behavior based on Time of Use pricing. The cost-based method involves period division based on the changing characteristics of actual supply costs over time [29]. This includes methods such as the day–load curve cost sudden change division method, cost time membership function method, and short-term marginal cost method, with a complex cost accounting process. Hierarchical clustering can merge loads into layers, providing a certain flexibility. This paper adopts the hierarchical clustering method to divide periods based on typical load curves and equivalent load curves.

3.2. Price Elasticity

The prerequisite for optimizing Time of Use pricing is to establish a response relationship model between user electricity consumption and electricity price. Typically, demand response uses price elasticity coefficients to describe this relationship, as they quantify the degree to which electricity consumption adjusts in response to price changes.

Price elasticity coefficients can be divided into self-elasticity coefficients and cross-elasticity coefficients [30,31]. The self-elasticity coefficient measures the immediate responsiveness of electricity consumption within the same time period to changes in its price, while the cross-elasticity coefficient captures the inter-period impact of price changes in one period to the consumption in another period. Specifically, price elasticity coefficients can be expressed as:

$$\varepsilon(t,t) = \frac{\Delta L_t / L_{0,t}}{\Delta P_t / P_{0,t}} \tag{6}$$

$$\varepsilon(t,h) = \frac{\Delta L_t / L_{0,t}}{\Delta P_h / P_{0,h}} \tag{7}$$

where $L_{0,t}$ is the electricity consumption in period t before responding; $P_{0,t}$ and $P_{0,h}$ are the electricity prices in period t and h before responding; ΔL_t is the relative change in electricity consumption in period t; ΔP_t and ΔP_h are the relative changes in electricity prices in periods t and h, respectively; $\varepsilon(t,t)$ is the self-elasticity coefficient. A higher self-elasticity value indicates that consumers are more sensitive to price changes, potentially leading to significant shifts in consumption patterns based on price variations. This sensitivity can be leveraged to flatten peak demand or fill valley hours by adjusting prices accordingly; $\varepsilon(t,h)$ is the cross-elasticity coefficient, which represents how price changes in one period can influence consumption behaviors in other periods. During the dispatch cycle, the self-elasticity coefficient and cross-elasticity coefficient are typically represented in matrix form as a price elasticity matrix for Time of Use pricing design.

In order to calculate price elasticity coefficients to estimate demand response, regression models are typically employed by fitting historical consumption and price data. These models analyze how changes in price influence consumer behavior over time, providing insights into the sensitivity of demand relative to price changes.

3.3. Demand Response Model

The idealized demand response model based on the price elasticity assumes that elasticity coefficients are the same in the same period. In reality, demand response by electricity users is influenced not only by electricity prices but also by factors such as the industry and individual characteristics of electricity users. With the steady growth of electricity consumption due to economic development in China, the average electricity price is gradually decreasing. Figure 6 shows the logarithm of the power grid load and the time series of electricity prices for each month in a certain location over four consecutive years. The gray line represents the grid load, the blue diagonal line represents the growth trend, the orange line represents the stabilized grid load after removing the trend component, and the yellow line represents the average electricity price. Figure 6 reveals an upward trend in overall grid load alongside a downward trend in average electricity prices. However, focusing solely on the correlation between electricity consumption and prices may overlook the inherent growth in consumption driven by economic expansion. Conclusions drawn from the rise in consumption attributed solely to price reductions can be biased, potentially exaggerating the responsiveness of electricity users to price changes.

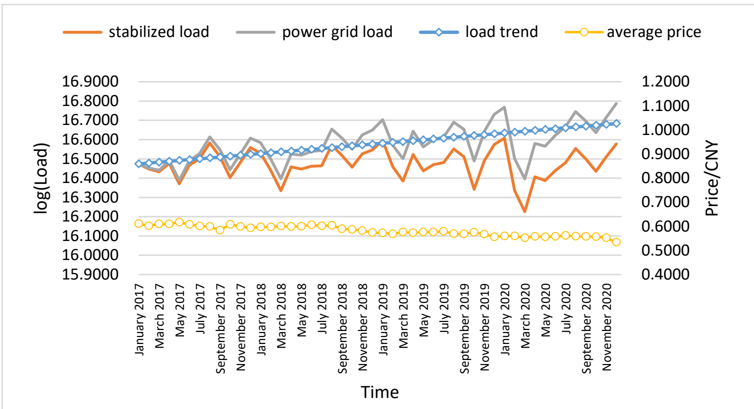

Figure 6. Trend of electricity load and price.

To overcome the limitations mentioned above, this paper establishes a user demand response model after removing the natural growth trend based on electricity prices and electricity user consumption data.

$$L_t = \alpha_0 t + \alpha_1 \tag{8}$$

$$L_t{}' = L_t - \Delta L_t \times (t-1) \tag{9}$$

$$L_t{}' = \beta_0 P + \beta_1 \tag{10}$$

In these formulas, L_t is the average load at time t, assuming that the load linearly increases over time and can be represented as a linear function of t. ΔL_t is the increment of the load at time t relative to the load at $(t-1)$. $L_t{}'$ is the stabilized load after removing the natural growth trend, as shown in Formula (9). $lnL_t{}'$ is the logarithmic value of the stabilized load $L_t{}'$, assuming $lnL_t{}'$ is a linear function of the electricity price P. The parameters α_0, α_1, β_0, β_1 in Formulas (8)–(10) can be obtained through regression analysis based on the historical data of grid load $L_t{}'$ and electricity price P. Therefore, as long as an electricity price P is set for a certain period, the grid load for that period can be obtained using Formula (10).

Figure 7 illustrates the causal relationship between load and electricity price. By analyzing user demand response through a model derived from monthly grid load data (on a logarithmic scale) and electricity price data over a continuous four-year period in a specific location, and after adjusting for natural growth trends, the relationship can be expressed as: $lnL_t{}' = -0.259P + 16.624$. The coefficient for P is -0.259, which signifies a negative correlation between load and electricity price. This indicates that as electricity prices rise, there is a corresponding decrease in the user-side load.

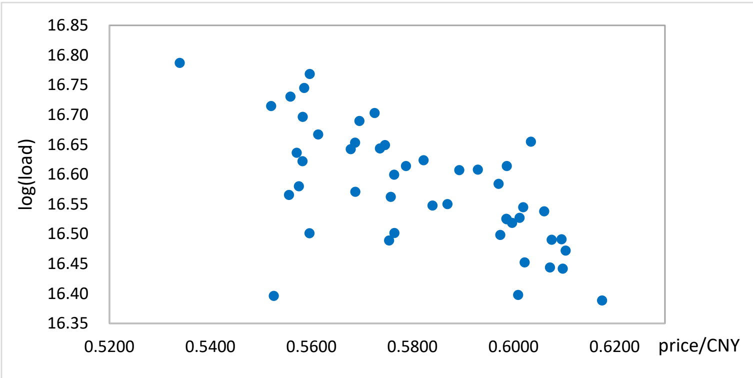

Figure 7. Demand response of users' load with respect to electricity price.

To assess the fitness of the demand response regression model, Table 1 presents a model test summary containing crucial statistical metrics necessary for evaluating the accuracy and reliability of the model.

Table 1. Demand response regression model summary.

R	R Squared	Adj. R Squared	RMSE	D–W	AIC	BIC	F	*p*
0.653	0.426	0.414	0.074	1.829	−109.470	−105.728	34.139	<0.001

The correlation coefficient (R) is 0.653, indicating a moderate correlation. The coefficient of determination (R Squared) is 0.426, meaning that approximately 42.6% of the variance in the load is explained by the electricity price. The adjusted R^2, slightly lower at 0.414, still supports a moderate explanatory power. The Root Mean Square Error (RMSE) of 0.074 indicates that the model predictions deviate from the actual values by this amount on average, suggesting a reasonable fit of the model to the data. Further statistical measures enhance the understanding of the model's performance and reliability. The Durbin–Watson (D–W) statistic is 1.829, which is closer to 2, suggesting that there is less evidence of positive autocorrelation among the residuals, and thus the residuals are more independent from one another. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values are −109.470 and −105.728, respectively, both suggesting that the model is a good fit. The model's significance is strongly supported by the F-statistic (34.139) and its associated p-value (<0.001), indicating that the model is statistically significant.

4. Time of Use Pricing Optimization Model

Time of Use (TOU) pricing is a crucial measure to leverage price signals, achieve peak–load shifting, alleviate power supply–demand conflicts, and promote the consumption of renewable energy. The design of TOU pricing must consider the interests of the generation side, supply side, and users, aiming to maximize total revenue or minimize costs, while ensuring that the interests of all participants are not harmed, to truly fulfill its role as a price signal.

4.1. Objective Function and Decision Variables

TOU pricing optimization is a multi-objective planning problem [32,33]. Optimization goals include maximizing the utilization of renewable energy, minimizing environmental governance costs, reducing the purchasing cost of electricity on the generation side, and minimizing the peak–valley difference in grid load. Some objectives are mutually consistent, while others conflict. For example, a high utilization rate of renewable energy reduces carbon emissions and lowers environmental governance costs, but whether the total purchasing cost of electricity on the generation side decreases depends on the power structure and the actual generation cost of different sources. For multi-objective planning problems, some objectives can be placed in the constraint conditions, and solutions can then be carried out.

In this paper, the total generation-side cost C_T is minimized as the optimization goal, while the goals of increasing the utilization rate of renewable energy and reducing the peak–valley difference in grid load are considered as constraints, along with constraints related to electricity balance, user-side tariff stability, and maintaining a reasonable peak-to-valley price ratio.

The total cost on the power supply side, in addition to the purchase costs of renewable energy such as wind power and photovoltaic power generation, and non-renewable energy such as coal, oil, and gas, also includes the environmental management costs brought by thermal power generation [34]. The objective function is represented as follows:

$$\min C_T = P_r Q_r + (P_c + P_e) Q_c \tag{11}$$

where C_T is the total generation-side cost, Q_r and Q_c are the total electricity consumption of renewable energy and thermal power generation after implementing peak–valley TOU pricing, P_r is the guiding price for renewable energy, P_c is the benchmark price for thermal power, and P_e is the environmental governance cost per unit of thermal power generation. The purchasing cost of renewable energy is computed by multiplying the guiding price by the amount of renewable energy consumption, while the purchasing and environmental governance costs of non-renewable energy (typically thermal power) are computed by adding the benchmark price to the product of the environmental governance cost and the amount of thermal power generation.

$$Q_r = \sum_{s \in T_s} Q_{rs} + \sum_{p \in T_p} Q_{rp} + \sum_{f \in T_f} Q_{rf} + \sum_{v \in T_v} Q_{rv} \tag{12}$$

$$Q_c = \sum_{s \in T_s} Q_{cs} + \sum_{p \in T_p} Q_{cp} + \sum_{f \in T_f} Q_{cf} + \sum_{v \in T_v} Q_{cv} \tag{13}$$

Here, T_s, T_p, T_f, and T_v represent the different time periods for sharp, peak, flat, and valley loads, respectively.

The electricity consumption Q_i, during the i-th hour under the electricity price P_i, is expressed as follows:

$$Q_i = L_i \times T_i = e^{\beta_0 P_i + \beta_1} \times T_i \tag{14}$$

where the electricity price P_i is a function $f(.)$ of the sharp, peak, flat, and valley electricity prices P_s, P_p, P_f and P_v, respectively:

$$P_i = f\left(P_s, P_p, P_f, P_v, i\right) \tag{15}$$

The renewable energy and thermal power grid electricity consumption during the i-th hour, Q_{ri} and Q_{ci}, are determined by the dispatch strategy represented by the function $g(\cdot)$:

$$Q_{ri} = g(L_i, r) \times T_i \tag{16}$$

$$Q_{ci} = g(L_i, c) \times T_i \tag{17}$$

Here, i represents the i-th hour of a 24 h day, T_i is the duration of the i-th hour (with a value of 1), L_i is the grid load during the i-th hour, Q_i is the user-side electricity consumption during the i-th hour under the electricity price P_i, β_0 and β_1 are obtained through regression analysis based on historical electricity price and load data according to the demand response model in Equation (10), and the time period during the i-th hour is determined using the hierarchical clustering method described in Section 2.1. The electricity price P_i is determined by the function $f(\cdot)$, and the dispatch strategy is represented by the function $g(\cdot)$, which determines the output of renewable energy units and non-renewable energy units based on the grid load L_i. The values of Q_{ri} and Q_{ci} are then obtained using Equations (16) and (17). The decision variables of the TOU pricing optimization model are the sharp, peak, flat, and valley electricity prices, i.e., P_s, P_p, P_f and P_v.

4.2. Constraint Conditions

(1) Reduction in Peak–Valley Difference

To achieve peak–load shaving and stabilize the system load, the TOU pricing mechanism mandates a reduction in the peak–valley difference of the grid load before and after optimization. This is quantified in Equation (18):

$$(\max L_{TOU} - \min L_{TOU}) \leq (\max L_0 - \min L_0) \tag{18}$$

where L_{TOU} refers to the grid load during various time periods after TOU pricing optimization, and L_0 refers to the grid load during various time periods before TOU pricing optimization. The rationale behind this constraint is to ensure that the load distribution becomes more uniform, reducing the strain on grid resources and infrastructure during peak times.

(2) Increase in Renewable Energy Utilization

To promote the consumption of renewable energy, it is required that the utilization rate of renewable energy is increased after TOU pricing optimization, i.e.,:

$$\sum_{i \in R} \sum_{j \in T} Q_{ij}^{TOU} \geq \sum_{i \in R} \sum_{j \in T} Q_{ij}^{0} \tag{19}$$

where Q_{ij}^0 and Q_{ij}^{TOU} are the consumption amounts of the i-th type of renewable energy during the j-th time period before and after TOU pricing optimization, respectively. This condition is set to ensure that the TOU pricing model actively promotes the use of renewable energy sources, aligning with broader environmental goals and sustainability practices.

(3) Electricity Balance

Assuming TOU pricing optimization does not change the total daily electricity consumption, the following equation holds:

$$\sum_{i \in T} Q_i^0 = \sum_{j \in T} Q_j^{TOU} \tag{20}$$

where Q_i^0 is the electricity consumption of various user types during time period i before peak–valley TOU pricing optimization, and Q_j^{TOU} is the electricity consumption during time period i after optimization. The introduction of the equivalent load curve may result in slight variations in the divisions of time periods before and after optimization, but the overall daily consumption remains constant to ensure energy balance and prevent any unintended increase in total energy usage.

(4) No Increase in User-Side Electricity Costs

TOU pricing optimization is viable only if it does not lead to an increase in the total electricity cost for users. Assuming the total electricity consumption remains unchanged before and after optimization, the average electricity price on the user side should not rise, as expressed in Equation (21):

$$\sum_{i \in U} \sum_{j \in T} P_{ij}^{TOU} Q_{ij}^{TOU} \leq \sum_{i \in U} \sum_{j \in T} P_{ij}^{0} Q_{ij}^{0} \tag{21}$$

where P_{ij}^{TOU} and Q_{ij}^{TOU} are the electricity price and consumption of the i-th user type during the j-th time period after TOU pricing optimization. This constraint ensures that the TOU pricing strategy is economically neutral for consumers, fostering acceptance and compliance without imposing additional financial burdens.

(5) Maintaining a Reasonable Peak-to-Valley Price Ratio

To ensure that the peak-to-valley price difference in electricity rates does not lead to excessive user reactions or insufficient response due to an unclear difference, it is crucial to maintain this ratio within a reasonable range. This is articulated in Equation (22):

$$\begin{cases} P_s > P_p > P_f > P_v > 0 \\ k_1 \leq \frac{P_p}{P_v} \leq k_2 \\ k_3 \leq \frac{P_s}{P_p} \leq k_4 \\ \frac{P_p - P_f}{P_f} \geq k_5 \\ \frac{P_f - P_v}{P_f} \geq k_6 \end{cases} \tag{22}$$

Here, parameters k_1 and k_2 restrict the peak-to-valley electricity price ratio, k_3 and k_4 restrict the ratio of sharp to peak electricity prices, and k_5 and k_6 restrict the fluctuation of peak and valley electricity prices based on flat-rate electricity prices. The notice "[2021]1093" from the National Development and Reform Commission (NDRC) provides specific requirements for the peak-to-valley electricity price difference and ratio: In regions where the predicted peak-to-valley ratio of the grid load exceeds 40% in the previous or current year, the price difference between peak and valley electricity rates should not be less than 4:1 in principle; in other regions, it should generally not be less than 3:1. The sharp electricity price should typically be increased by at least 20% above the peak-period electricity prices. According to the national implementation of Time of Use (TOU) pricing, the peak electricity prices are generally raised by 15% to 85% compared to flat-rate prices, sharp electricity prices are further increased by 20% to 25% above the peak rates, and valley electricity prices are reduced by 20% to 70% below flat-rate prices. Given the current landscape, and to allow for flexibility in adjustments, the parameters can be set as follows: $k_1 = 3$, $k_2 = 10$, $k_3 = 1.2$, $k_4 = 2$, $k_5 = 0.1$ and $k_6 = 0.2$.

This constraint ensures that TOU pricing remains effective and adaptable, promoting energy conservation and efficient use without causing undue stress or confusion among consumers.

4.3. The Social Network Search (SNS) Algorithm

The above Time of Use (TOU) pricing optimization model is calculated using a recent metaheuristic algorithm known as the Social Network Search (SNS) algorithm. As detailed in [35], the SNS algorithm was applied to solve various challenging optimization problems. The results demonstrate that SNS is highly capable of managing diverse optimization scenarios, consistently outperforming other algorithms. The SNS algorithm incorporates four innovative optimization operators: Imitation, Conversation, Disputation, and Innovation. These operators, referred to as "moods", are designed to mimic the real-world behaviors of social network users when they express their opinions, thereby enhancing the algorithm's effectiveness in solving complex problems.

4.3.1. Imitation

The Imitation mood is characterized by users' tendency to emulate others' expressions and viewpoints. This mood captures the essence of social learning, where individuals are influenced by the perspectives of their peers, often leading to a homogenization of thoughts and ideas within the network. This mental state can be represented quantitatively as follows:

$$X_{inew} = X_j + rand(-1,1) \times rand(0,1) \times \left(X_i - X_j\right) \quad (23)$$

where X_j represents the vector of the j-th user's view which is selected randomly and $i \neq j$, X_i is the vector of the i-th user's view. X_{inew} is the user's new location in the search space. Also, $rand(0,1)$ and $rand(-1,1)$ indicate two random vectors in intervals [0, 1] and [−1, 1], respectively.

4.3.2. Conversation

Conversely, the Conversation mood facilitates a more interactive exchange where users engage in dialogues, sharing and refining their thoughts through direct communication. This mood supports a collaborative environment where knowledge is co-created and shared among participants. This mental state can be represented as follows:

$$X_{inew} = X_k + rand(0,1) \times sign\left(f_i - f_j\right) \times \left(X_j - X_i\right) \quad (24)$$

where X_k demonstrates the vector of the issue which is randomly chosen to speak about it, X_j is the vector of a randomly selected user's view for a chat and X_i is the vector of view of the ith user, and it should be noted that $i \neq j \neq k$ in which j and k are selected randomly. In addition, $sign$ is the sign function and $sign\left(f_i - f_j\right)$ determines the moving direction of X_k.

4.3.3. Disputation

In the Disputation mood, users are inclined to engage in debates and discussions, often challenging and defending various viewpoints. This mood is crucial for the critical examination of ideas, fostering a platform where arguments can be tested and validated through collective scrutiny. The new impacted view can be expressed as follows:

$$X_{inew} = X_i + rand(0,1) \times \left(\frac{\sum_t^{N_r} X_t}{N_r} - (1 + round(rand)) \times X_i\right) \quad (25)$$

where the symbol ($round$) rounds the real input to the adjacent integer number, whereas the symbol (N_r) represents the group size or commenters.

4.3.4. Innovation

Lastly, the Innovation mood is observed when users initiate discussions based on novel ideas or personal experiences. As a result, a new concept will be generated, and the new impacted viewpoint may be expressed as follows:

$$\begin{gathered} x_{inew}^d = t \times x_j^d + (1 - t) \times n_{new}^d \\ n_{new}^d = lb_d + rand_1 \times (ub_d - lb_d) \\ t = rand_2 \end{gathered} \quad (26)$$

where d is the d-th variable that is selected randomly in the interval [1, D], and D is the number of problem's variables. $rand_1$ and $rand_2$ are two random numbers in the interval [0, 1]. Also, ub_d and lb_d are the maximum and minimum values for the d-th variable. n_{new}^d represents the new idea about the d-th dimension of the problem. x_j^d is the current idea about the d-th variable presented by another user, (j-th represents the user selected randomly and $i \neq j$) and i-th shows the user wants to change it because of new idea

(n^d_{new}). Finally, the new view about the d-th dimension will be created as x^d_{inew}. x^d_{inew} is an interpolation of the current idea (x^d_j) and the new idea (n^d_{new}).

A change in one dimension (x^d_{inew}) causes a general change in the main concept, and can be considered as a new view to share. This process can be modeled as follows:

$$X_{inew} = \left[x_1, x_2, x_3, \ldots x^d_{inew} \ldots x_D\right] \tag{27}$$

where x^d_{inew} is a new insight into the issue under consideration from the d-th viewpoint, and is replaced with the current view (x^d_i).

4.3.5. Rules and Implementation of SNS Algorithm

As illustrated in [35], the method is produced by various moods, where each user's viewpoint is altered, and fresh views are utilized based on their merit. If the new idea is superior to the existing one, it will be approved. As a result, the value of a new concept may be determined by the objective function of X_{inew}, which can be calculated analytically and compared to the value of an existing thought (X_i) as follows:

$$\mathrm{X}_i = \begin{cases} X_i, & f(X_i) < f(X_{inew}) \\ X_{inew}, & f(X_{inew}) \geq f(X_i) \end{cases} \tag{28}$$

The implementation of the Social Network Search (SNS) algorithm unfolds across three phases: initialization, increasing popularity, and checking terminating conditions.

During the initialization phase, the algorithm sets up the initial conditions and parameters, establishing a baseline from which the search begins. The increasing popularity phase involves the propagation of ideas or solutions. This phase is critical as it determines the direction and momentum of the search process. Finally, the checking terminating conditions phase evaluates whether the search has met the predefined criteria, which would signal the completion of the algorithm's execution. This structured approach ensures that the algorithm systematically explores the solution space, efficiently optimizing towards the best possible outcomes.

5. Case Analysis

5.1. Basic Data

This section validates the effectiveness of the TOU pricing optimization model using typical daily load data from a specific period in the northern region of the State Grid. The renewable energy output data is presented in Table 2. The average utilization rate of renewable energy is 95.08%, with renewable energy generation accounting for 15.90%.

Table 2. Output and consumption of renewable energy in a power grid area of China.

Time	Renewable Energy Output/MW	Renewable Energy Consuming Load/MW	Renewable Energy Usage Rate	Renewable Energy Proportion
00:00	3492.29	3275.90	93.80%	14.66%
01:00	3283.07	3065.97	93.39%	13.93%
02:00	3230.80	3094.89	95.79%	14.15%
03:00	2952.94	2801.40	94.87%	13.03%
04:00	2792.09	2645.10	94.74%	12.06%
05:00	2882.21	2716.75	94.26%	11.91%
06:00	2782.50	2657.42	95.50%	11.34%
07:00	2894.47	2762.11	95.43%	11.37%
08:00	3172.81	2984.25	94.06%	12.23%
09:00	3953.16	3792.74	95.94%	15.74%
10:00	5332.17	5007.10	93.90%	20.94%

Table 2. *Cont.*

Time	Renewable Energy Output/MW	Renewable Energy Consuming Load/MW	Renewable Energy Usage Rate	Renewable Energy Proportion
11:00	6060.23	5701.89	94.09%	24.84%
12:00	6088.68	5730.08	94.11%	24.82%
13:00	5897.45	5600.63	94.97%	23.94%
14:00	5535.37	5220.15	94.31%	22.75%
15:00	4410.08	4236.63	96.07%	17.83%
16:00	2809.71	2683.14	95.50%	10.53%
17:00	2818.42	2715.48	96.35%	10.53%
18:00	3129.57	3005.72	96.04%	12.09%
19:00	3344.11	3170.38	94.80%	12.59%
20:00	3653.51	3536.35	96.79%	14.30%
21:00	4009.13	3845.02	95.91%	15.86%
22:00	4634.98	4516.13	97.44%	19.23%
23:00	5308.70	5056.85	95.26%	22.52%

5.2. Results

5.2.1. Time Period Division Results Based on Equivalent Load

The equivalent load is computed based on Equation (4). The traditional division based on typical loads includes 3 h in the sharp period from 16:00 to 18:00 and 19:00 to 20:00, 6 h in the peak period, 7 h in the flat period, and 8 h in the valley period. Keeping the cumulative duration of sharp, peak, flat, and valley periods unchanged, the division is recomputed using the hierarchical clustering method based on the equivalent load. As shown in Table 3, the results of the time period division between 05:00 and 06:00 changed from valley to flat, while they changed from flat to valley between 11:00 and 12:00, as indicated in bold.

Table 3. Typical load and equivalent load and corresponding time period division.

Time	Typical Load /MW	Equivalent Load /MW	Time Period Based on Typical Load	Time Period Based on Equivalent Load
00:00–01:00	22,345.87	22,687.40	valley	valley
01:00–02:00	22,002.30	22,457.81	valley	valley
02:00–03:00	21,874.76	22,350.26	valley	valley
03:00–04:00	21,507.32	22,119.14	valley	valley
04:00–05:00	21,934.15	22,491.49	valley	valley
05:00–06:00	**22,818.01**	**23,179.97**	**valley**	**flat**
06:00–07:00	23,438.28	23,686.03	flat	flat
07:00–08:00	24,299.29	24,349.42	peak	peak
08:00–09:00	24,410.55	24,391.57	peak	peak
09:00–10:00	24,090.94	23,968.30	peak	peak
10:00–11:00	23,916.54	23,575.81	flat	flat
11:00–12:00	**22,950.37**	**22,661.71**	**flat**	**valley**
12:00–13:00	23,088.40	22,765.67	flat	flat
13:00–14:00	23,394.45	23,036.29	flat	flat
14:00–15:00	22,942.89	22,756.39	valley	valley
15:00–16:00	23,762.03	23,613.79	flat	flat
16:00–17:00	25,479.33	25,305.09	sharp	sharp
17:00–18:00	25,791.04	25,546.42	sharp	sharp
18:00–19:00	24,863.28	24,747.40	peak	peak
19:00–20:00	25,181.11	24,965.96	sharp	sharp
20:00–21:00	24,721.92	24,524.04	peak	peak
21:00–22:00	24,237.13	24,073.72	peak	peak
22:00–23:00	23,489.37	23,338.40	flat	flat
23:00–00:00	22,454.81	22,402.05	valley	Valley

Rows with changed period division are indicated in bold.

5.2.2. Comparative Analysis of Solution Algorithms

The Social Network Search (SNS) algorithm is implemented to solve the problem described in Section 4. In order to evaluate the performance of the SNS algorithm, we performed a comparative analysis against two other prominent optimization algorithms: Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). This analysis spanned 100 iterations. Figure 8 illustrates the comparative results of these algorithms.

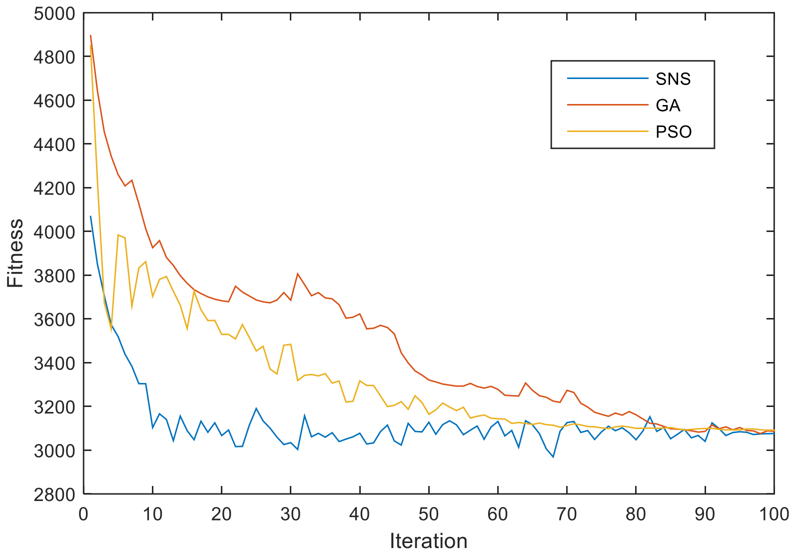

Figure 8. Comparison of optimization algorithm performance.

The performance comparison based on the Figure 8 is outlined as follows:

(1) Initial Performance

SNS starts at the lowest value, indicating the most effective initial condition among the three algorithms in minimizing the load difference. PSO and GA begin at a higher value than SNS, suggesting a less effective initial performance.

(2) Rate of Convergence

SNS shows a rapid improvement in the initial iterations, quickly reducing the load difference, which suggests a strong initial convergence towards an optimal solution. PSO decreases steadily but at a slower rate compared to SNS, indicating a moderate rate of convergence. GA also shows a decrease but remains higher than SNS throughout the iterations, indicating a slower convergence compared to SNS.

(3) Stability and Final Performance

All three algorithms begin to stabilize after about 30 iterations, with gradual improvements as iterations continue. SNS maintains the lowest values throughout the process, indicating that it consistently finds solutions with the smallest load differences, suggesting the best overall optimization performance.

(4) Final Convergence

Towards the final iterations (around 80 to 100), all algorithms show minimal changes, indicating convergence. SNS and PSO appear to converge at a similar level, which is better than GA.

In summary, SNS appears to be the most effective algorithm, offering the best optimization performance with the most stable convergence.

5.2.3. TOU Pricing Optimization Results

Before the Time of Use (TOU) pricing optimization, the electricity prices for each period in the region were as follows: 0.9699 CNY for sharp, 0.8082 CNY for peak, 0.5388 CNY for flat, and 0.2694 CNY for valley. However, due to changes in the characteristics of the power system load, it became necessary to adjust these TOU prices for optimization.

The equivalent load method was utilized, beginning with the calculation of the optimized equivalent load curve as defined by Equation (4). Subsequently, considering the consumption of renewable energy, the TOU pricing optimization model was solved using the SNS algorithm. As previously discussed in Section 2.1, Time of Use (TOU) pricing can be improved through optimization tailored to various grid load curves. To assess the effectiveness of the TOU pricing optimization method based on equivalent load, we performed a comparative analysis of TOU electricity pricing before and after optimization using different load models: typical load, net load, and equivalent load. This analysis is presented in Table 4, which displays the electricity prices for four distinct time periods—sharp, peak, flat, and valley—across four different scenarios.

Table 4. TOU pricing design based on typical load, net load and equivalent load.

Price/CNY	Before Optimization	Based on Typical Load	Based on Net Load	Based on Equivalent Load
Sharp price	0.9699	1.2279	1.2324	1.2313
Peak price	0.8082	0.8186	0.8216	0.8208
Flat price	0.5388	0.5388	0.5388	0.5388
Valley price	0.2694	0.1500	0.1500	0.1500
Sharp-valley price difference	0.7000	1.0779	1.0824	1.0813

Initially, the sharp price was 0.9699 CNY, which increased across all models after optimization, with the highest being 1.2324 CNY for the net load and a slightly lower optimized equivalent load price of 1.2313 CNY. The peak price saw a modest increase from the original 0.8082 CNY to 0.8208 CNY in the equivalent load model. The flat price remained constant at 0.5388 CNY across all scenarios. The valley price, however, saw a significant reduction from 0.2694 CNY to 0.1500 CNY in all optimized scenarios, reflecting a strategic decrease to encourage off-peak consumption.

The sharp–valley price difference before optimization was 0.7000 CNY, which increased notably in all scenarios post-optimization, with the equivalent load model showing a difference of 1.0813 CNY. The increased sharp–valley price difference post-optimization is a strategic move to enhance demand response. By widening the cost gap between the highest and lowest demand times, the TOU pricing encourages consumers to shift their usage to off-peak times, thus aiding in grid stability and efficient energy use.

Table 5 provides a detailed analysis of the effects of TOU pricing optimization on various key metrics, comparing the values before and after optimization using three different load models.

Table 5. Impacts of TOU pricing optimization based on typical load, net load and equivalent load.

Items	Before Optimization	Based on Typical Load		Based on Net Load		Based on Equivalent Load	
		Value	Increased	Value	Increased	Value	Increased
Cost of power generation/10,000 CNY	21,504.56	21,502.50	−2.06	21,502.19	−2.37	21,502.07	−2.49
Renewable energy consumption/MWh	89,822.08	91,422.55	1600.47	91,658.80	1836.72	91,757.64	1935.56
Utilization rate of renewable energy/%	95.08%	96.78%	1.69%	97.03%	1.94%	97.13%	2.05%

Initially, the cost of power generation was 21,504.56 × 10,000 CNY. After optimization, the costs were slightly reduced across all models. The equivalent load model achieved the lowest cost at 21,502.07 × 10,000 CNY, showing a decrease of 2.49 × 10,000 CNY. These reductions indicate that the equivalent load model effectively lowers the cost of power generation.

Regarding renewable energy consumption, it was initially 89,822.08 MWh. Post-optimization, the equivalent load model observed the highest increase to 91,757.64 MWh, up by 1935.56 MWh. This metric shows that TOU pricing optimization not only reduces costs but also significantly boosts renewable energy consumption, with the greatest increase achieved with the equivalent load model.

The utilization rate of renewable energy was 95.08% before optimization. After optimization, the equivalent load model reached the highest at 97.13%, an increase of 2.05%. The equivalent load model again shows the most substantial improvement, aligning with the increases in renewable energy consumption and reductions in generation costs.

5.3. Impacts Analysis

5.3.1. Impacts on Consumer Side

(1) Division Reflects the Output Level of Renewable Energy

Based on the division results presented in Table 3, a time period change graph is plotted in Figure 9. The division, which is based on the equivalent load curve, generally aligns with the division based on typical load. However, there are some variations during periods of low renewable energy output (5:00–6:00) and high output (11:00–12:00).

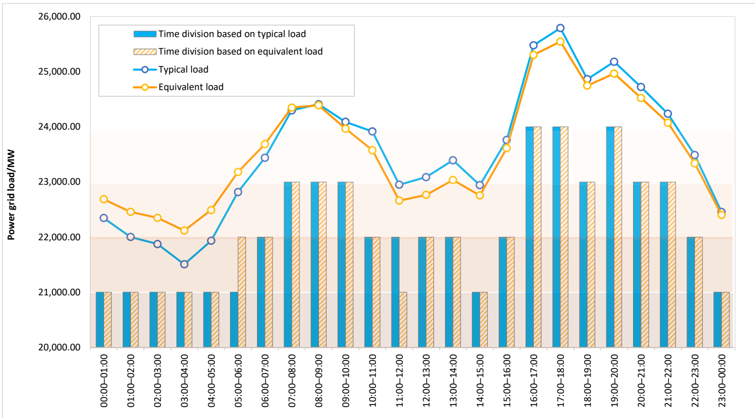

Figure 9. Time period division based on traditional method and equivalent load.

During the period of low renewable energy output (5:00–6:00), the equivalent load is higher, causing this period to shift from the valley to the flat period. Conversely, during the period of high renewable energy output (11:00–12:00), the equivalent load is lower, causing this period to shift from the flat to the valley period. Although the typical load during the period of high renewable energy output (11:00–12:00) is higher than during the period of low output (5:00–6:00), the equivalent load during the period of high output is lower. This results in users being charged valley prices during the period of high output, which helps to release demand and promote the consumption of renewable energy.

(2) Further Widening of Sharp–Valley Price Difference

The initial sharp–valley price difference was 0.7 CNY, with a sharp–valley ratio of 2.6. Following the optimization process, which utilized the equivalent load, net load, and typical load methods, prices during sharp and peak periods experienced a significant increase, while prices during the valley period decreased substantially. Figure 10 illustrates that the sharp–valley price difference achieved through the equivalent load method is 1.0813 CNY, with a sharp–valley ratio of 8.2. This represents a notable 3.6 times increase compared to the pre-optimization state, thereby enhancing price adjustment flexibility and strengthening the demand response from consumers.

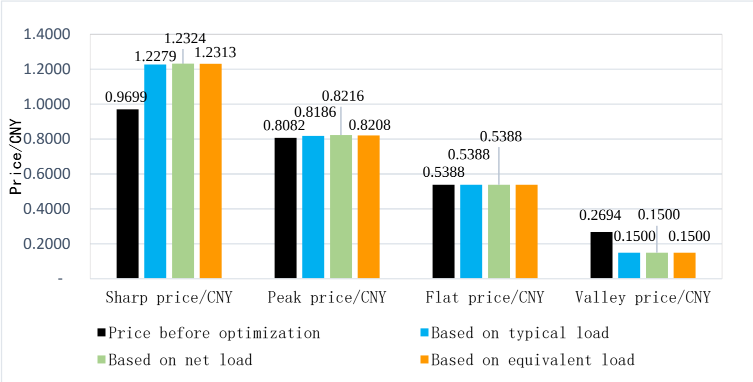

Figure 10. TOU pricing design based on typical load, net load and equivalent load.

5.3.2. Impacts on Supply Side

Figure 11 presents the load changes on the supply side following the optimization of the Time of Use electricity price based on typical load, net load, and equivalent load. The results demonstrate substantial peak-cutting and valley-filling effects on the load on the supply side, as detailed below:

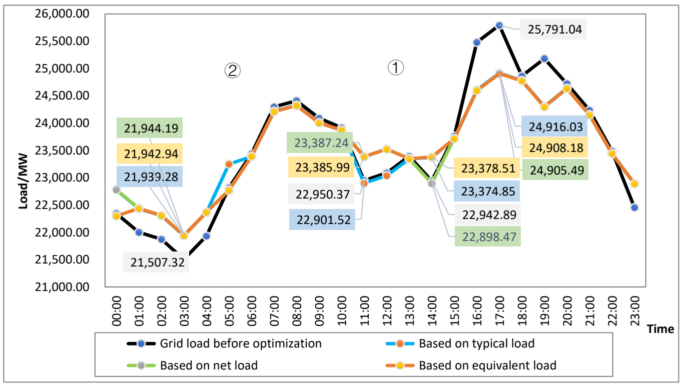

Figure 11. Daily load curve before and after TOU pricing optimization.

(1) Reduction in Peak Load

In Figure 11, the black line represents the typical load curve before optimization, the blue line represents the power grid load curve after optimization using the typical load method, and the green line represents the power grid load curve after optimization based on the net load. After optimizing the equivalent load curve, the new curve remains the equivalent load, which needs to be restored to the power grid load curve, represented by the orange curve in Figure 11. It is evident that all three optimization methods effectively reduce the highest load of the power grid. The highest load of the power grid is reduced from 25,791.04 MW to 24,916.03 MW, resulting in a peak reduction of 875.01 MW using the typical load method. The net load optimization reduces the highest load to 24,905.49 MW, achieving a peak reduction of 885.85 MW. After optimization based on the equivalent load, the highest load is further reduced to 24,908.18 MW, achieving a peak reduction of 882.86 MW. The peak-cutting effects of the three methods are relatively similar.

(2) Decrease in Sharp–Valley Load Difference

Table 6 provide a comprehensive analysis of the effects of TOU pricing optimization on sharp–valley load difference related to the power supply side.

The sharp–valley load difference was initially 4283.72 MW. After optimization, it decreased to 2976.75 MW with the typical load model (a reduction of 1306.97 MW), to 2961.30 MW with the net load model (a reduction of 1322.42 MW), and to 2965.24 MW with the equivalent load model (a reduction of 1318.48 MW). These significant reductions indicate that TOU pricing optimization effectively smooths out the load curve, reducing the disparity between the highest and lowest loads, which can lead to more efficient grid operation and less need for rapid ramping of power generation resources.

Table 6. Impacts at power supply side of TOU pricing optimization based on typical load, net load and equivalent load.

Items	Before Optimization	Based on Typical Load		Based on Net Load		Based on Equivalent Load	
		Value	Increased	Value	Increased	Value	Increased
Maximum load of grid/MW	25,791.04	24,916.03	−875.01	24,905.49	−885.55	24,908.18	−882.86
Minimum load of grid/MW	21,507.32	21,939.28	431.96	21,944.19	436.87	21,942.94	435.62
Sharp-valley load difference/MW	4283.72	2976.75	−1306.97	2961.30	−1322.42	2965.24	−1318.48

It is worth noting that during periods with more renewable energy output (area ① in Figure 11), only the grid supply load after optimization by the equivalent load method is higher and more stable, indicating that the output structure of the power source side has effectively been transmitted to the supply side, which can promote the power system to transition from "source follows load" to "source–load interaction".

The sharp–valley load difference is further presented in Figure 12, which illustrates that the TOU pricing optimization, particularly when based on the equivalent load model, effectively manages the power supply side by reducing peak loads, increasing minimum loads, and smoothing the load differences, thereby enhancing grid stability and operational efficiency.

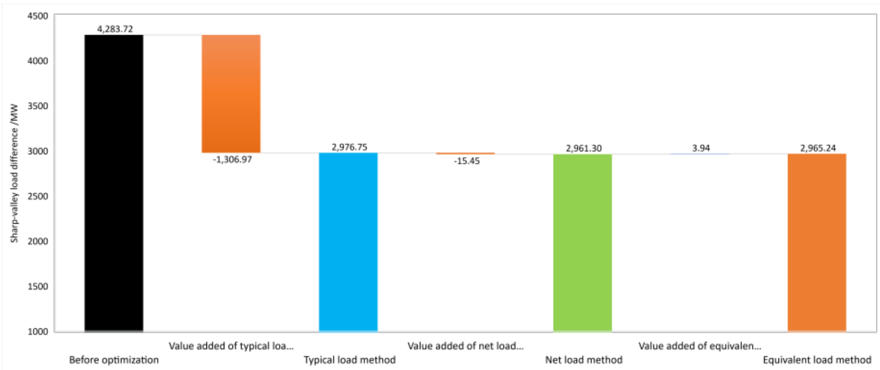

Figure 12. Effects of TOU pricing optimization on peak valley load differences.

5.3.3. Impacts on Generation Side

Figure 13 visually illustrates the impact of Time of Use (TOU) pricing optimization on renewable energy consumption before and after applying three different optimization methods: typical load, net load, and equivalent load. This bar chart clearly shows the incremental increases in renewable energy consumption resulting from each method, providing a quantitative comparison of their effectiveness.

The baseline scenario is represented by a black bar, showing the renewable energy consumption at 89,822.08 MWh before any optimization. The subsequent bars in cyan, green and orange represent the renewable energy consumption after optimization using the typical load, net load, and equivalent load methods, respectively.

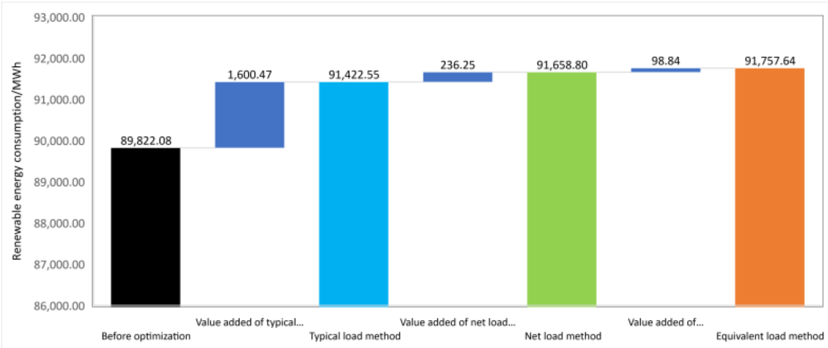

Figure 13. Renewable energy consumption changes before and after TOU pricing optimization.

The cyan bar for the typical load method shows an increase in renewable energy consumption to 91,422.55 MWh, which is an increase of 1600.47 MWh from the baseline. The green bar for the net load method indicates a further increase to 91,658.80 MWh. The most significant increase is shown by the orange bar for the equivalent load method, with renewable energy consumption rising to 91,757.64 MWh. This is an increase of 1935.56 MWh from the baseline, marking the highest improvement among the three methods.

In summary, the optimization of Time of Use (TOU) pricing through methods based on typical load, net load, and equivalent load all yield benefits such as peak shaving, valley filling, reduced peak–valley load difference, lower generation-side costs, and increased consumption of renewable energy. Notably, the net load and equivalent load methods outperform the traditional typical load method. The net load method slightly outperforms in terms of peak shaving and valley filling. However, the equivalent load method effectively aligns the output structure from the power generation side to the power supply side, resulting in a significant reduction in generation side costs and a more pronounced promotion of renewable energy consumption.

6. Conclusions

This paper introduces an innovative concept of equivalent load and proposes an optimized Time of Use (TOU) pricing optimization model from a demand response perspective, validated using power load data from a northern region of the national power grid of China. The analysis comprehensively assesses the impacts across the electricity consumer side, supply side, and generation side, revealing significant benefits.

The findings indicate that optimizing TOU pricing by widening the peak-to-valley price difference on the consumer side enhances price adjustment flexibility. On the supply side, the equivalent load method effectively reduces the maximum grid load and narrows the peak-to-valley load difference, contributing to a more stable grid load. Additionally, on the generation side, it lowers average generation costs and boosts the consumption of renewable energy.

The proposed TOU pricing optimization method, based on equivalent load, stands out from existing methods that rely on typical grid load and net load due to several distinctive features:

(1) Demand-Side and Generation-Side Linkage: The TOU electricity price based on equivalent load aligns demand-side user response with renewable energy consumption on the generation side. This promotes a transition in the power system from "source following load changes" to "source–load interaction," enhancing the dynamic balance between supply and demand.

(2) Enhanced Renewable Energy Utilization: By incorporating the power grid load, renewable energy responsibility weight, and renewable energy consumption, the equivalent load approach significantly enhances the utilization rate of renewable energy, especially in regions with high renewable output.

(3) Economic and Environmental Benefits: The equivalent load TOU pricing optimization method reduces generation side costs without increasing consumer costs. It supports peak shaving and valley filling, benefiting multiple stakeholders across the source and load sides. This contributes positively to the clean and low-carbon transformation of the power system, and supports the achievement of dual carbon goals.

Additionally, the implementation of the Social Network Search (SNS) algorithm in solving the TOU pricing optimization model based on equivalent load further enhances the method's effectiveness. The SNS algorithm, known for its robustness and efficiency in handling complex optimization problems, ensures that the pricing strategy is not only responsive to changes in demand and supply but also optimally aligned with the operational dynamics of the power grid.

Overall, the use of the equivalent load model, coupled with the SNS algorithm, demonstrates a sophisticated approach to integrating renewable energy metrics into pricing strategies, aiming to optimize both economic and environmental outcomes in the power sector. This method not only improves system efficiency and stability but also aligns with broader environmental objectives, marking a significant step forward in the sustainable evolution of power systems.

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