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Real-Time Pricing Model of Smart Grid Under Dual-Carbon Target Based on Social Welfare Maximisation

Abstract. *In the context of China's dual carbon goals and the new electricity reform, new energy has achieved a leap-forward development. However, the large-scale and high proportion of new energy connection and consumption pose new challenges to the power system. Regarding new energy power's randomness and intermittence, while traditional energy power's stable and controllability, it is important to make full use of the complementarity of the two types of electricity power. The aggregated power supplier,who provides both traditional energy power and new energy power, is considered in this paper. Imposing two-way penalties on traditional energy power, i.e., carbon governance costs on the supply side and guilt costs on the demand side, can promote the effective consumption of new energy power. A social welfare maximisation model for a smart grid system composed of an aggregated power supplier and multiple users is established, and a distributed RTP algorithm is designed too. Finally, a numerical simulation analysis is conducted. It is found that the price of new energy power is always lower and that new energy power is fully consumed, which effectively alleviates the energy shortage and environmental pollution caused by relying solely on traditional energy supply.*

Keywords: *real-time price, carbon governance, guilt cost, social welfare.*

JEL Classification: D6.

1. Introduction

With the gradual depletion of traditional energy sources, such as oil and coal, and the intensification of environmental pollution, new energy sources are receiving more and more attention due to their cleanliness, environmental protection, and renewability. According to statistics from the National Energy Administration of China, China's cumulative installed power generation capacity in 2023 is about 2.92 billion kilowatts, a year-on-year increase of 13.9%. Among them, the installed capacity of solar power generation is about 0.61 billion kilowatts, a year-on-year increase of 55.2%. The total installed capacity of new energy generation is 1.53 billion kilowatts, which has exceeded the thermal power installed capacity of 1.39 billion kilowatts. In this practical context, how to promote the effective consumption of new energy has become a critical and urgent issue. Considering the inherent randomness and intermittency of new energy sources such as wind and solar energy,

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their power generation can only be predicted in advance and cannot be effectively controlled. However, traditional energy generation technologies are mature, stable, and easy to control. Therefore, the integrated energy system with complementary power supply between new energy and traditional energy is regarded as an important form of energy supply in the future (Li et al., 2020; Ma et al., 2021). However, relying solely on market self-regulation cannot effectively solve the supply-demand balance problem in integrated energy systems. Demand Side Management (DSM), as an effective power management tool, provides ideas for this issue. Demand Response (DR) is one of the solutions for DSM, which guides users to actively transfer or reduce loads based on price signals by adjusting electricity prices or using compensation methods, ultimately achieving the goal of energy conservation and efficient use, while ensuring the safe, reliable, and stable operation of the power grid (Gao,2022). The core of DR is the price response. How to fully leverage the signaling role of electricity prices and guide users to use electricity off-peak can not only effectively ensure the balance of supply and demand in the power system, but also has great positive significance for promoting the accelerated development of new energy, effective consumption, and achieving carbon peaking and carbon neutrality goals.

In recent years, the pricing issue of power products has been widely concerned and studied (Li & Gao, 2023; Samadi et al., 2010; Zhang & Sun, 2023; Wang et al., 2022; Zhang et al., 2022; Zhu et al., 2022; Qu et al., 2022). The electricity pricing mechanism based on DR mainly includes time-of-use pricing (TOU), critical-peak pricing (CPP), and real-time pricing (RTP). RTP is the cost that occurs at a certain moment during the use of electricity, reflecting the instantaneous demand. It is considered to be the most effective pricing mechanism and one of the most ideal pricing mechanisms in the future smart grid environment (Gao,2022). Research on RTP is carried out mainly from two points of view. One is to consider the social attributes of electricity, where a social welfare maximisation model is established (Yuan et al.,2021; Li et al.,2022; Rawat et al.,2022; Chiu et al.,2017; Luo & Gao,2022). The other is to consider the commodity properties of electricity, where a game model is established to take the equilibrium price of supply and demand as RTP (Tang et al.,2016; Wu et al.,2021; Zhu et al., 2022; Dipti et al., 2017). However, most existing research is based on the assumption of rational individuals, only considering economic benefits and not highlighting carbon reduction in the model. In fact, with the continuous improvement of education level, electricity users may feel guilty when using traditional energy, such as thermal power, because the production of electricity from traditional energy deviates from the national dual carbon goals (Wang et al.,2019). In order to fulfil the commitments to the world, one of the effective measures in the comprehensive energy electricity market is to use price signals to guide users to scientifically and reasonably use electricity, promoting the effective consumption of new energy. However, current research on the synergistic and complementary power supply of traditional energy and new energy mostly assumes that the prices of the two types of electricity are the same (Li et al.,2020; Wang et al., 2022; Gao & Gao, 2023). In fact, the same price makes it difficult for users to choose new energy power products according to the price signals, which results in the ineffective role of electricity price signals.

Different from the existing studies, this paper considers both the cost of carbon emission management at the supply side and the guilt cost of using traditional energy power at the demand side, which makes the model more relevant to China's reality. The remainder of this paper is organised as follows. In section 2, a mathematical formulation of system model is formulated. In section 3, a distributed algorithm for RTP is designed. In section 4, the numerical simulation results are presented.

2. System model

Consider a smart grid system that includes an aggregated power supplier, n users, and a Power Market Scheduling Center (PMSC), where $\mathsf{N} = \{1, 2, \ldots, n\}$ is the user set. Aggregated power supplier provides both traditional and new energy power. Traditional energy power uses fossil fuels, such as coal, to generate electricity, and its output value can be effectively controlled. New energy power is mainly composed of wind power and photovoltaic power, and its output value can be predicted in advance according to climate conditions, but cannot be effectively controlled. The PMSC conducts bidirectional information exchange with the power supplier and users through communication networks. Divide an electricity cycle into K time periods, where $\mathsf{K} = \{1, 2, \ldots, K\}$ is the set of time periods. At the beginning of each time period, PMSC broadcasts electricity prices. Users optimise their electricity consumption based on the received electricity price signals to determine their demand. The power supplier determines the traditional energy generation capacity based on the received electricity price signals on account of the full consumption of new energy electricity, and then provides total power supply. PMSC updates the electricity price based on the received electricity demand and supply information, and broadcasts the updated electricity price again. Based on the new electricity price information received, users and the aggregated power supplier will redefine their electricity demand and supply and provide feedback to PMSC until supply and demand balance is achieved, and the electricity price is determined. At that time, the electricity price is the RTP for that period. The interaction relationship of this smart grid system can be represented by Figure 1, where the red solid lines represent the power transmission line and the blue dashed lines represent the information transmission line.

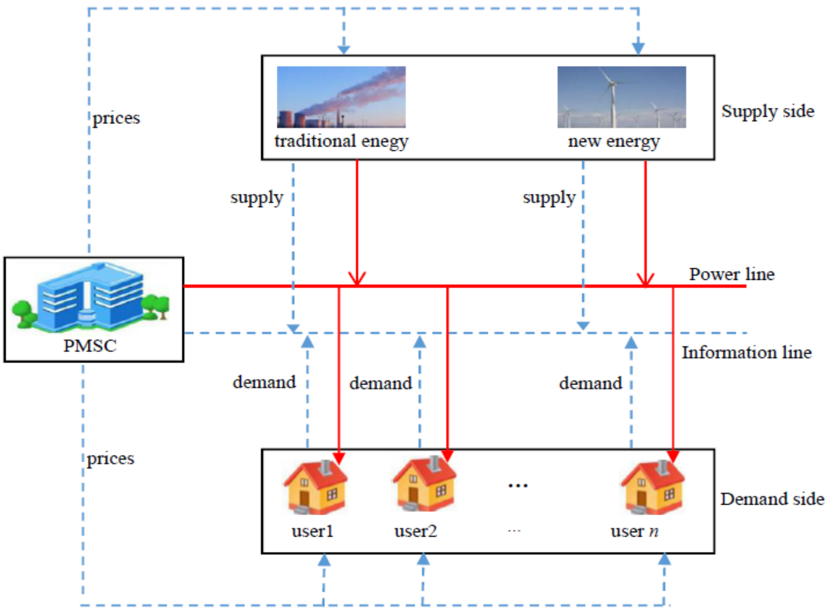

Figure 1. Power system interactions

Source: The images (PMSC,Users and power plant)are from the web, others are drawn by authors based on Microsoft word.

Let $x_i^{k,T}$ and $x_i^{k,N}$ denote the traditional energy and new energy power consumption of the user i in the period k, respectively. Then the total power consumed by the user i in the period k is

$$x_i^k = x_i^{k,T} + x_i^{k,N}, \tag{1}$$

where $m_i^k \le x_i^k \le M_i^k$, m_i^k 、 M_i^k are the minimum and maximum consumption of the user i in the kth period. Let L_k^T be the traditional energy supply during the period k, which satisfies

$$L_k^{T,\min} \le L_k^T \le L_k^{T,\max}, \tag{2}$$

where $L_k^{T,\min}$ and $L_k^{T,\max}$ are the minimum and maximum traditional energy supply in the period$k$.Let L_k^N be the new energy power supply in the period k , which satisfies

$$L_k^N \sim N(\mu_k, \sigma_k^2), \tag{3}$$

where μ_k and σ_k^2 are the mean and variance of the new energy power supply in the period k.

2.1 Demand-Side Analysis

Users purchase electricity from the aggregated power supplier to meet their own electricity needs. Their benefits include the following three parts:

The first part is the users' satisfaction obtained through the consumption of electricity. The utility function in microeconomics is commonly used to measure this satisfaction. The utility function $U(x)$ satisfies two basic assumptions of non-decreasing and diminishing marginal utility, namely $\frac{dU(x)}{dx} \geq 0$, $U(0) = 0$ and $\frac{d^2U(x)}{dx^2} \leq 0$. Like the most power system pricing models, the following piecewise function [5] is adopted as the utility function:

$$U_T(x_i^{k,T}, w_i^{k,T}) = \begin{cases} w_i^{k,T} x_i^{k,T} - \frac{\alpha_i^k}{2}\left(x_i^{k,T}\right)^2, & 0 \leq x_i^{k,T} \leq \frac{w_i^{k,T}}{\alpha_i^k} \\ \frac{\left(w_i^{k,T}\right)^2}{2\alpha_i^k}, & x_i^{k,T} \geq \frac{w_i^{k,T}}{\alpha_i^k} \end{cases} \tag{4}$$

$$U_N(x_i^{k,N}, w_i^{k,N}) = \begin{cases} w_i^{k,N} x_i^{k,N} - \frac{\alpha_i^k}{2}\left(x_i^{k,N}\right)^2, & 0 \leq x_i^{k,N} \leq \frac{w_i^{k,N}}{\alpha_i^k} \\ \frac{\left(w_i^{k,N}\right)^2}{2\alpha_i^k}, & x_i^{k,N} \geq \frac{w_i^{k,N}}{\alpha_i^k} \end{cases} \tag{5}$$

where $\alpha_i^k, w_i^{k,T}$ and $w_i^{k,N}$ are non-negative constants, $U_T(x_i^{k,T}, w_i^{k,T})$ and $U_N(x_i^{k,N}, w_i^{k,N})$ represent the utility of user *i*'s consumption of conventional energy power and new energy power during period *k* respectively. $U(x_i^k, w_i^k) = U_T(x_i^{k,T}, w_i^{k,T}) + U_N(x_i^{k,N}, w_i^{k,N})$ denotes the total utility of user *i* during period *k*.

The second part is the electricity charge that the users need to pay the supplier, which is denoted as C_i^k . Suppose that the prices of traditional energy power and new energy power in the period *k* are p_T^k and p_N^k respectively, then the electricity expenditure of the user *i* in the period *k* is:

$$C_i^k = p_T^k \cdot x_i^{k,T} + p_N^k \cdot x_i^{k,N} . \tag{6}$$

The third part is the users' guilty cost. With the improvement of residents' education level and the enhancement of national ownership awareness, facing China's solemn commitment to the world's carbon peak and carbon neutrality, users will feel guilty about the environmental pollution caused by carbon emissions in the traditional energy power generation process. Assume that users feel guilty only when they use traditional power. $C_{i,g}^k(x_i^{k,T}, g_i^k)$ is used to represent the guilty cost when the user i uses $x_i^{k,T}$ traditional energy power in the time period k, where $g_i^k > 0$ is the user's guilt coefficient. According to Wang et al. (2019), we take

$$C_{i,g}^k(x_i^{k,T}, g_i^k) = g_i^k \cdot (x_i^{k,T})^2, \tag{7}$$

where $C_{i,g}^k(x_i^{k,T}, g_i^k)$ satisfies $\frac{\partial C_{i,g}^k(x_i^{k,T})}{\partial x_i^{k,T}} \geq 0$, $\frac{\partial C_{i,g}^k(x_i^{k,T}, g_i^k)}{\partial g_i^k} \geq 0$, $\frac{\partial^2 C_{i,g}^k(x_i^{k,T})}{\partial \left(x_i^{k,T}\right)^2} \geq 0$ and $C_{i,g}^k(0, g_i^k) = 0$.

In summary, the total welfare of the user side is

$$W_i^k = U(x_i^k, w_i^k) - C_i^k - C_{i,g}^k(x_i^{k,T}, g_i^k).$$

2.2 Supply Side Analysis

The aggregated power supplier provides two types of power and generates profits by selling electricity to users. Supplier's benefits include the following four parts:

The first part is the revenue obtained by the power supplier through the sale of electricity. The electricity revenue of the power supplier during period k is exactly the electricity purchase cost of all electricity users $\sum_{i=1}^{n} C_i^k = \sum_{i=1}^{n} \left(p_T^k \cdot x_i^{k,T} + p_N^k \cdot x_i^{k,N} \right)$.

The second part is the generation cost of the power supplier by producing L_k^T traditional energy electricity, which is denoted as $C_k^1(L_k^T)$. According to the physical characteristics of thermal power generation, the cost of power generation is usually described by a monotonically increasing quadratic convex function (Gao,2022; Samadi et al., 2010; Wang et al., 2022), i.e,

$$C_k^1(L_k^T) = a_k \left(L_k^T\right)^2 + b_k L_k^T + c_k, \tag{8}$$

where $a_k > 0$, $b_k, c_k \geq 0$ and a_k, b_k, c_k are constants.

The third part is the carbon tax that power supplier needs to pay for producing L_k^T traditional energy power, which is denoted as $C_k^1(L_k^T)$. According to Wang et al. (2022), the actual carbon emission of L_k^T is $Q^C = r\left(L_k^T\right)^2 + sL_k^T + t$, where r, s, $t$are the carbon emission factors.According to the carbon governance mechanism that emitters pay, power supplier needs to pay a certain carbon tax due to producing traditional energy electricity. Let the carbon tax price per ton of carbon dioxide be p^C, then the carbon tax that the power supplier needs to pay is

$$C_k^2(L_k^T) = p^C \cdot Q^C = p^C \cdot \left[r\left(L_k^T\right)^2 + sL_k^T + t \right]. \tag{9}$$

The fourth part is the equipment maintenance cost required by the power supplier to produce L_k^N new energy power, which is denoted as $C_k^3(L_k^N)$. Since wind energy, solar energy, and other natural resources used in new energy power generation do not need to pay costs, the raw material cost is ignored, and only the maintenance cost of new energy power generation equipment is considered. According to Wang et al. (2022), take

$$C_k^3(L_k^N) = \theta\left(L_k^N\right)^2 + \eta L_k^N, \tag{10}$$

where $\theta > 0, \eta \geq 0$ are the equipment maintenance cost coefficients.

In summary, the total revenue of the power supply side is

$$R^k = \sum_{i=1}^{n} C_i^k - C_k^1(L_k^T) - C_k^2(L_k^T) - C_k^3(L_k^N).$$

2.3 Social welfare maximisation model

The social welfare maximisation model of the system composed of the demand side and the supply side can be expressed as:

$$\begin{aligned}
\max\ & \sum_{k=1}^{K}\left\{\sum_{i=1}^{n}[U(x_i^k, w_i^k) - C_{i,g}^k(x_i^{k,T})] - C_k^1(L_k^T) - C_k^2(L_k^T) - C_k^3(L_k^N)\right\} \\
s.t.\ & \sum_{i=1}^{n} x_i^{k,T} \leq L_k^T,\ k = 1,2,\ldots,K \\
& P\left(\sum_{i=1}^{n} x_i^{k,N} \leq L_k^N\right) \geq 1-\beta,\ k = 1,2,\ldots,K \\
& (1)-(10)
\end{aligned} \tag{11}$$

where β is a small positive number. $P\left(\sum_{i=1}^{n} x_i^{k,N} \leq L_k^N\right) \geq 1-\beta$ is the probability constraint, which indicates that the probability that the new energy power used does not exceed the generation is not lower than $1-\beta$. The probability constraint should be first transformed into a deterministic constraint for the convenience of solving. Assume $L_k^N \sim N(\mu_k, \sigma_k^2)$, then $P\left(\sum_{i=1}^{n} x_i^{k,N} \leq L_k^N\right) \geq 1-\beta$ can be equivalently transformed into $\sum_{i=1}^{n} x_i^{k,N} \leq \mu_k + \sigma_k \Phi^{-1}(\beta)$, where $\Phi^{-1}(\beta)$ is the quantile of the standard normal distribution. Thus, Equation (11) can be expressed as

$$\max \sum_{k=1}^{K}\left\{\sum_{i=1}^{n}[U(x_i^k, w_i^k) - C_{i,g}^k(x_i^{k,T})] - C_k^1(L_k^T) - C_k^2(L_k^T) - C_k^3(L_k^N)\right\}$$
$$s.t. \quad \sum_{i=1}^{n} x_i^{k,T} \le L_k^T,\ k = 1,2,\ldots,K$$
$$\sum_{i=1}^{n} x_i^{k,N} \le \mu_k + \sigma_k \Phi^{-1}(\beta),\ k = 1,2,\ldots,K$$
$$(1)-(10) \tag{12}$$

Obviously, the objective function of problem (12) is concave, and the constraint set is composed of linear inequalities or bound constraints, so the constraint set is convex, and problem (12) is a convex programming problem, which can be effectively solved by traditional convex programming techniques. It is noted that the decision variables in (12) include user's electricity consumption $x_i^{k,T}$ 、 $x_i^{k,N}$ and the supplier's power supply L_k^T 、 L_k^N , butRTP, which is the core variable of the problem, is not shown in the model, so a direct solution is invalid. There are two common transformation strategies: one is to write the KKT system of problem (12), and obtain the Lagrange multiplier (shadow price in economics) as RTP by solving the KKT system; the other is to use duality theory and obtain RTP by solving the dual problem. Solving the KKT system is a centralised algorithm, which needs to obtain the electricity consumption preference of all users in advance. However, the centralised algorithm has two disadvantages. On the one hand, it is not conducive to protecting the privacy of users. On the other hand, if there are a large number in users, the increase of the dimension of the decision variables of the problem will bring great difficulties to the solution, which cannot meet the essential requirements of the rapid response of RTP. Therefore, the dual method is adopted to solve the problem (12) in this paper.

3. RTP algorithm based on duality theory

It is noted that each period in (12) is independent, so a distributed algorithm can be used. The optimisation problem corresponding to the *k*th period of (12) can be formulated as follows:

$$\max \sum_{i=1}^{n}[U(x_i^k, w_i^k) - C_{i,g}^k(x_i^{k,T})] - C_k^1(L_k^T) - C_k^2(L_k^T) - C_k^3(L_k^N)$$
$$s.t. \quad \sum_{i=1}^{n} x_i^{k,T} \le L_k^T$$
$$\sum_{i=1}^{n} x_i^{k,N} \le \mu_k + \sigma_k \Phi^{-1}(\beta)$$
$$(1)-(10) \tag{13}$$

The Lagrangian function of (13) is

$$L(x_i^{k,T},x_i^{k,N},L_k^T,L_k^N;\lambda_k^T,\lambda_k^N)=\sum_{i=1}^{n}[U(x_i^k,w_i^k)-C_{i,g}^k(x_i^{k,T})]-C_k^1(L_k^T)-C_k^2(L_k^T)-C_k^3(L_k^N)$$
$$+\lambda_k^T\left[L_k^T-\sum_{i=1}^{n}x_i^{k,T}\right]+\lambda_k^N\left(\mu_k+\sigma_k\Phi^{-1}(\beta)-\sum_{i=1}^{n}x_i^{k,N}\right)$$
$$=\sum_{i=1}^{n}[U_T(x_i^{k,T},w_i^{k,T})+U_N(x_i^{k,N},w_i^{k,N})-C_{i,g}^k(x_i^{k,T})-\lambda_k^T x_i^{k,T}-\lambda_k^N x_i^{k,N}]$$
$$+\lambda_k^T L_k^T-C_k^1(L_k^T)-C_k^2(L_k^T)-C_k^3(L_k^N)+\lambda_k^N(\mu_k+\sigma_k\Phi^{-1}(\beta))$$

where $\lambda_k^T,\lambda_k^N\geq 0$ are Lagrangian multipliers. According to the saddle point theory, problem (13) can be transformed into:

$$\min_{\lambda_k^T,\lambda_k^N\geq 0}\ \max_{x_i^{k,T},\ x_i^{k,N},\ L_k^T,\ L_k^N} L(x_i^{k,T},x_i^{k,N},L_k^T,L_k^N;\lambda_k^T,\lambda_k^N)\,. \tag{14}$$

Let

$$x_i^{k,T,*}=\arg\max_{x_i^{k,T}}\left[U_T(x_i^{k,T},w_i^{k,T})-C_{i,g}^k(x_i^{k,T})-\lambda_k^T x_i^{k,T}\right], \tag{15}$$

$$x_i^{k,N,*}=\arg\max_{x_i^{k,N}}\left[U_N(x_i^{k,N},w_i^{k,N})-\lambda_k^N x_i^{k,N}\right], \tag{16}$$

$$L_k^{T,*}=\arg\max_{L_k^T}\left[\lambda_k^T L_k^T-C_k^1(L_k^T)-C_k^2(L_k^T)\right], \tag{17}$$

$$L_k^{N,*}=\arg\max_{L_k^N}\left[\lambda_k^N(\mu_k+\sigma_k\Phi^{-1}(\beta))-C_k^3(L_k^N)\right], \tag{18}$$

$$D(\lambda_k^T,\lambda_k^N)=\max_{x_i^{k,T},\ x_i^{k,N},\ L_k^T,\ L_k^N} L(x_i^{k,T},x_i^{k,N},L_k^T,L_k^N;\lambda_k^T,\lambda_k^N)$$
$$=\sum_{i=1}^{n}[U_T(x_i^{k,T,*},w_i^{k,T})+U_N(x_i^{k,N,*},w_i^{k,N})-C_{i,g}^k(x_i^{k,T,*})-\lambda_k^T x_i^{k,T,*}-\lambda_k^N x_i^{k,N,*}]$$
$$+\lambda_k^T L_k^{T,*}-C_k^1(L_k^{T,*})-C_k^2(L_k^{T,*})-C_k^3(L_k^{N,*})+\lambda_k^N(\mu_k+\sigma_k\Phi^{-1}(\beta))\,.$$

The gradient projection algorithm can be used to solve the dual problem $\min_{\lambda_k^T,\lambda_k^N\geq 0} D(\lambda_k^T,\lambda_k^N)$:

$$\lambda_k^{T,\,t+1}=\lambda_k^{T,\,t}+\gamma_k^{T,\,t}d_k^{T,\,t}\ , \tag{19}$$

$$\lambda_k^{N,\,t+1}=\lambda_k^{N,\,t}+\gamma_k^{N,\,t}d_k^{N,\,t}\ , \tag{20}$$

where t represents the number of iterations, $\gamma_k^{T,t},\gamma_k^{N,t}\geq 0$ represent the step sizes, and $d_k^{T,t}$ 、 $d_k^{N,t}$ are descent directions of $D(\lambda_k^T,\lambda_k^N)$. Let

$$d_k^{T,t}=-\frac{\partial D(\lambda_k^T,\lambda_k^N)}{\partial\lambda_k^{T,t}}=\sum_{i=1}^{n}x_i^{k,T,*}-L_k^{T,*}\ , \tag{21}$$

$$d_k^{N,t} = -\frac{\partial D(\lambda_k^T, \lambda_k^N)}{\partial \lambda_k^{N,t}} = \sum_{i=1}^{n} x_i^{k,N,*} - \mu_k - \sigma_k \Phi^{-1}(\beta). \tag{22}$$

Equation (21) shows that when $\sum_{i=1}^{N} x_i^{k,T,*} > L_k^{T,*}$, $d_k^{T,t} > 0$, $\lambda_k^{T,t+1} > \lambda_k^{T,t}$. From the perspective of economics, when the demand of traditional energy exceeds the supply, the price of traditional energy electricity rises. Conversely, when $\sum_{i=1}^{N} x_i^{k,T*} < L_k^{T,*}$, $d_k^{T,t} < 0$, $\lambda_k^{T,t+1} < \lambda_k^{T,t}$. That is, when the supply of traditional energy exceeds the demand, the price of traditional energy electricity falls. When $\sum_{i=1}^{N} x_i^{k,T,*} = L_k^{T,*}$, $\lambda_k^{T,t+1} = \lambda_k^{T,t}$. That is, when supply and demand are balanced, the electricity price of traditional energy reaches equilibrium and remains unchanged. Equation (22) shows that, when $\sum_{i=1}^{n} x_i^{k,N,*} > \mu_k + \sigma_k \Phi^{-1}(\beta)$, $d_k^{N,t} > 0$, $\lambda_k^{N,t+1} > \lambda_k^{N,t}$. From the perspective of economics, if the demand of new energy electricity exceeds the forecast threshold $\mu_k + \sigma_k \Phi^{-1}(\beta)$, the price of new energy electricity increases. On the contrary, when the demand of new energy electricity is lower than the predicted threshold $\mu_k + \sigma_k \Phi^{-1}(\beta)$, the price of new energy electricity decreases. When $\sum_{i=1}^{n} x_i^{k,N,*} = \mu_k + \sigma_k \Phi^{-1}(\beta)$, the electricity price of new energy reaches equilibrium and remains unchanged.

According to Equations (15)-(16), each user can obtain the optimal electricity consumption by maximising his/her personal welfare. Equations (17)-(18) show that the supplier obtains the optimal power supply by maximising its revenue. To sum up, the specific algorithm (Algorithm 1) to solve problem (13) can be shown as follows.

Algorithm 1 Distributed algorithm for RTP

Step0: Initialise parameters. Given m_i^k 、 M_i^k 、 $L_k^{T,\min}$ 、 $L_k^{T,\max}$ 、 μ_k 、 σ_k 、 $w_i^{k,T}$ 、 $w_i^{k,N}$ 、 α_i^k 、 g_i^k 、 a_k 、 b_k 、 c_k 、 p^C 、 r 、 s 、 t 、 θ 、 η and the stop error ε. Let the cycle counter $t = 0$. The PMSC broadcasts $\lambda_k^{T,t}$ and $\lambda_k^{N,t}$ randomly to the demand side and supply side.

Step1: Demand side. Each user calculates the optimal $x_i^{k,T,*}(\lambda_k^{T,t})$ and $x_i^{k,N,*}(\lambda_k^{N,t})$ according to equations (15)-(16) based on the received electricity price $\lambda_k^{T,t}, \lambda_k^{N,t}$, and feeds back his/her optimal electricity consumption to PMSC;

Step2: Supply side. Supplier Calculates the optimal power supply $L_k^{T,*}(\lambda_k^{T,t})$ according to Equation (17) based on the received electricity price $\lambda_k^{T,t}$, and feeds back the predicted μ_k and σ_k to PMSC;

Step3: PSMC side. PMSC receives user's optimal electricity consumption $x_i^{k,T,*}(\lambda_k^{T,t})$, $x_i^{k,N,*}(\lambda_k^{N,t})$, supplier's optimal power supply $L_k^{T,*}(\lambda_k^{T,t})$, $L_k^{N,*}(\lambda_k^{N,t})$, and calculates $\lambda_k^{T,t+1}$ and $\lambda_k^{N,t+1}$ according to equations (19)-(20).

Step 4. Judgement. Judge whether

$$0 \le L_k^{T,*}(\lambda_k^t) - \sum_{i=1}^{N} x_i^{T,k,*}(\lambda_k^{T,t}) \le \varepsilon$$

and

$$0 \le \mu_k + \sigma_k \Phi^{-1}\left(\beta\right) - \sum_{i=1}^{n} x_i^{k,N,*} \le \varepsilon$$

are both satisfied.

If yes, let $\lambda_k^T = \frac{1}{2}\left(\lambda_k^{T,t} + \lambda_k^{T,t+1}\right)$, $\lambda_k^N = \frac{1}{2}\left(\lambda_k^{N,t} + \lambda_k^{N,t+1}\right)$, and get the real-time price λ_k^T and λ_k^N during *k*th period;

If not, let $\lambda_k^{T,t} \leftarrow \lambda_k^{T,t+1}$ and $\lambda_k^{N,t} \leftarrow \lambda_k^{N,t+1}$, and go to Step 1.

Most distributed RTP algorithms set the stopping criteria as follows (Gao, 2022; Li & Gao, 2023; Li et al., 2022; Ma et al., 2021):

$$\left|\lambda_k^{T,t+1} - \lambda_k^{T,t}\right| < \varepsilon .$$

This criterion cannot ensure that the power supplied is not less than the sum of the power demand of all users, which may cause disruption. Nevertheless, the stopping criteria given in this paper can ensure the stable operation of the power grid and meet the convergence of the electricity price.

4. Numerical simulation

The effectiveness of the model and algorithm proposed in this paper will be verified by numerical simulation in this section. Consider a smart grid system with 50 users, and an electricity consumption cycle (a day) is divided into 24 periods. Parameter values are set with reference to Wang et al. (2022) and Wang et al. (2019). Taking a representative period k as an example, let the user's utility parameter be $w_i^{k,T} \sim U(1,3)$, $w_i^{k,N} \sim U(1.5,4)$ and $\alpha_i^k = 0.5$, guilty coefficient be $g_i^k \sim U(0.08,0.16)$, cost coefficients of traditional energy power be $a_k = 0.01$, $b_k = 0$ and $c_k = 0$, coefficients of carbon emission be $r = 0.0034$, $s = -0.38$ and $t = 36$, carbon tax price be $p^C = 130$, coefficients of new energy power generation equipment's maintenance cost be $\theta = 0.01$ and $\eta = 0$, electricity price update step size be $\gamma_k^t = 0.01$, stopping error be $\varepsilon = 0.1$, the ith user's minimum and maximum electricity consumption during the$k$thperiod are $m_i^k = 1$ and $M_i^k = 3$, the minimum and maximum traditional energy power supply during the kth period are $L_k^{T,\min} = 50$ and $L_k^{T,\max} = 150$, the mean and standard deviation of the new energy power supply be $\mu_k = 80$ and $\sigma_k = 40$, let $\beta = 0.01$.

The simulation results for the prices of two types of energy at different iterations based proposed algorithm are depicted in Figure 2. Obviously, in the whole iteration process, the price of new energy power is always lower than that of traditional energy power, which can effectively promote the consumption of new energy electricity. Furthermore, the algorithm has a fast convergence speed, which can meet the inherent requirements of rapid response of RTP.

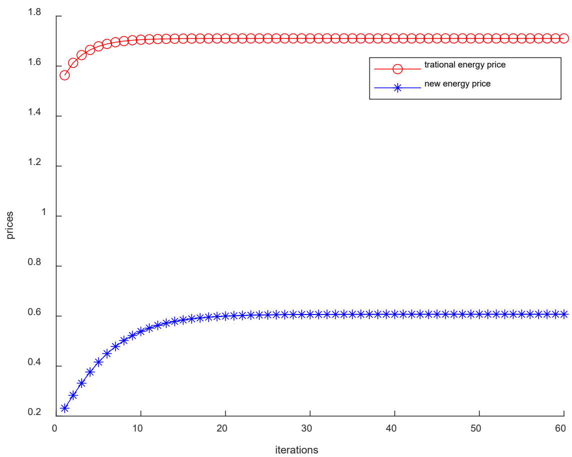

Figure 2. Relationship between electricity price and number of iterations
Source: Figure 2 is obtained by authors based on Matlab 2021b.

Figure 3 and Figure 4 give the supply and demand of traditional energy power, and new energy power respectively. In the process of determining the RTP, the supply of traditional energy power increases, and the demand of it decreases gradually, and they tend to be consistent quickly. Because the supply of new energy power depends on the actual situation of the natural environment, which can be predicted but not determined in advance, the supply of new energy power remains unchanged, and the demand of it declines rapidly until all the supply is consumed.

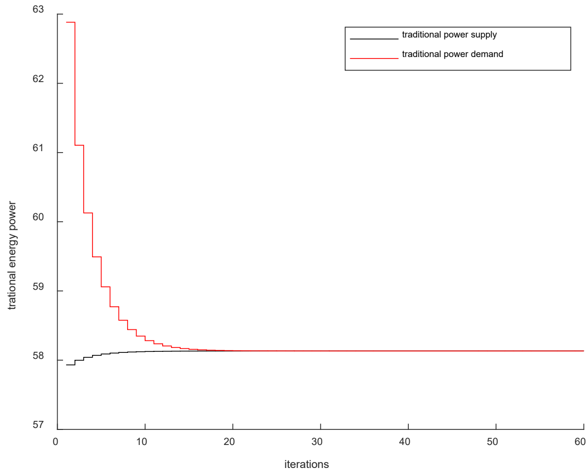

Figure 3. Relationship between power supply, demand and iterations of traditional energy sources

Source: Figure 3 is obtained by authors based on Matlab 2021b.

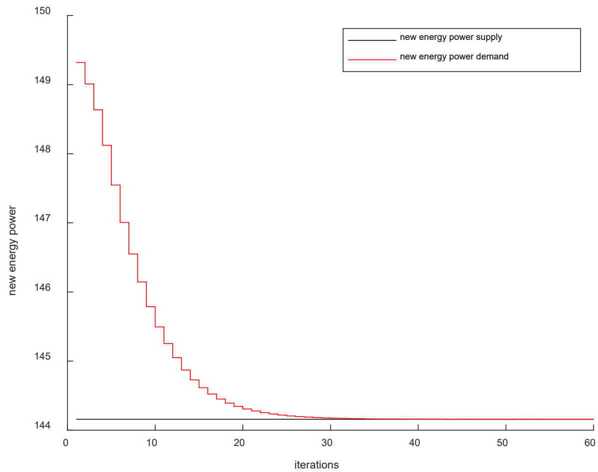

Figure 4. Relationship between supply, demand and iterations of new energy power

Source: Figure 4 is obtained by authors based on Matlab 2021b.

5. Conclusions

In the context of smart grids, in addition to hardware facilities, fully utilising price signals for DSM can effectively promote the consumption of new energy electricity, furthermore helping to achieve the dual carbon goals. On the demand side, different from the existing studies, this paper gives a greater preference for the consumption of new energy power in utility function, namely $w_i^{k,N} \geq w_i^{k,T}$,takes into account both the education level and patriotic enthusiasm of citizens, and considers the guilt cost caused by psychological effects when users consume traditional energy power. On the supply side, in addition to considering the conventional power generation cost, based on the principle of “Who emits, who controls”, the carbon emission control cost during the production of conventional energy electricity is added. The simulation results show that the user's consumption of new energy electricity can reach 100%. It can be seen that, besides using price signals for market regulation, joint governance by appropriately charging carbon governance costs on the supply side and improving citizens' sense of social responsibility on the demand side can effectively promote the priority consumption of new energy electricity, thereby promoting the achievement of China's dual carbon goals. However, this paper did not differentiate between different types of user. In fact, industrial users, as major electricity consumers, may have higher requirements for power stability. This issue will be studied next.

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