Capacity investment decisions of energy storage power stations supporting wind power projects

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Abstract

Purpose – Rapidly increasing the proportion of installed wind power capacity with zero carbon emission characteristics will help adjust the energy structure and support the realization of carbon neutrality targets. The intermittency of wind resources and fluctuations in electricity demand has exacerbated the contradiction between power supply and demand. The time-of-use pricing and supply-side allocation of energy storage power stations will help "peak shaving and valley filling" and reduce the gap between power supply and demand. To this end, this paper constructs a decision-making model for the capacity investment of energy storage power stations under time-of-use pricing, which is intended to provide a reference for scientific decision-making on electricity prices and energy storage power station capacity.

Design/methodology/approach – Based on the research framework of time-of-use pricing, this paper constructs a profit-maximizing electricity price and capacity investment decision model of energy storage power station for flat pricing and time-of-use pricing respectively. In the process, this study considers the dual uncertain scenarios of intermittency of wind resources and random fluctuations in power demand.

Findings – (1) Investment in energy storage power stations is the optimal decision. Time-of-use pricing will reduce the optimal capacity of the energy storage power station. (2) The optimal capacity of the energy storage power station and optimal electricity price are related to factors such as the intermittency of wind resources, the unit investment cost, the price sensitivities of the demand, the proportion of time-of-use pricing and the thermal power price. (3) The carbon emission level is affected by the intermittency of wind resources, price sensitivities of the demand and the proportion of time-of-use pricing. Incentive policies can always reduce carbon emission levels.

Originality/value – This paper creatively introduced the research framework of time-of-use pricing into the capacity decision-making of energy storage power stations, and considering the influence of wind power intermittentness and power demand fluctuations, constructed the capacity investment decision model of energy storage power stations under different pricing methods, and compared the impact of pricing methods on optimal energy storage power station capacity and carbon emissions.

Highlights

(1) Electricity pricing and capacity of energy storage power stations in an uncertain electricity market.
(2) Investment strategy of energy storage power stations on the supply side of wind power generators.

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(3) Impact of pricing method on the investment decisions of energy storage power stations.
(4) Impact of pricing method, energy storage investment and incentive policies on carbon emissions.
(5) A two-stage wind power supply chain including energy storage power stations.

Keywords Electric power investment, Capacity decision, Time-of-use pricing, Energy storage, Wind power generation

Paper type Research paper

1. Introduction

The large-scale emission of greenhouse gases, mainly carbon dioxide, increases the concentration of carbon dioxide in the atmosphere and is one of the main reasons for the rise in global temperatures, which promotes extreme disaster events such as high temperatures, droughts and heavy rains [1]. Countries worldwide thus agree on the need to reduce carbon dioxide emissions and lower the concentration of carbon dioxide in the atmosphere. According to Boao Forum's "Sustainable Asia and the World – Green Transition Asia in Action," as of the end of December 2021, 136 countries worldwide have set carbon neutrality targets. Since the announcement of the "Double Carbon Target" in September 2020, China has issued successive plans such as "Opinions on Completely, Accurately and Comprehensively Implementing the New Development Concept and Doing a Good Job in Carbon Peak Carbon Neutrality" and "Carbon Peak Action Plan before 2030," while various provinces and industries have issued corresponding carbon neutrality implementation plans. Among them, the power industry is one of the main sources of carbon emissions. According to the International Energy Agency, global carbon emissions from energy generation and heating reached 43% in 2020, much higher than the second-placed transportation and manufacturing sector [2]. China's carbon emissions in the field of power generation and heating account for up to 51% of total carbon emissions, with the high emission characteristics of fossil fuels being the most important reason for the high carbon emission intensity of the power generation industry. The vigorous development of renewable energy generation promoting the decarbonization and zero carbonization of electricity is the key to achieving carbon neutrality targets. To this end, in recent years, China has vigorously promoted renewable energy power generation projects represented by wind power and photovoltaics. By the end of 2021, China's installed renewable energy generation capacity had reached 10, 240 million kilowatts, and wind power and photovoltaic power generation installed capacity had increased by 180% compared with 2016. The proportion of total installed capacity increased by 12.97% [3].

However, wind and photovoltaic power generation are characterized by intermittentness, and power output varies at different times (Zhou *et al.*, 2018; Zhu *et al.*, 2021). Moreover, the distribution of wind and solar resources in China is seriously unbalanced, resulting in evident instability in the wind and photovoltaic power supply. At the same time, electricity demand cannot be interrupted, displays random fluctuations at different time and is affected by the adjustment of electricity prices. As such, there is an obvious imbalance in the supply and demand of renewable energy electricity and even the characteristics of reverse peak regulation, resulting in the long-term coexistence of power shortages and "wind curtailment" and "light curtailment." The vigorous development of the peak shaving auxiliary service market is the key to ensuring that renewable energy power is prioritized for grid integration and reducing the "wind curtailment rate" and "light curtailment rate"; that is, encouraging coal-fired units, energy storage power stations and other entities to actively participate in peak shaving and frequency regulation services to ensure power consumption. The government department has issued several documents intended to promote the development of the peak shaving auxiliary service market, and the "Work Plan for Improving the Compensation (Market) Mechanism for Electric Auxiliary Services" issued by the National Energy Administration stipulates that energy storage equipment and thermal power units are encouraged to carry out auxiliary power services [4]. The allocation of energy storage power stations on the supply side has become an important starting point for conducting renewable energy power peak shaving services. The "Guiding Opinions on Accelerating the Development of New Energy Storage" issued by the National Development and Reform Commission and the National Energy Administration highlights the need to build grid-side energy storage or wind and photovoltaic storage power stations and improve the peak–valley electricity price policy [5]. Qinghai Province directly stipulates that new energy projects should in principle have a proportion of energy storage capacity of no less than 10% [6].

"Peak shaving and valley filling" in the power market can be effectively realized by relying on the cooperation between energy storage power stations and time-of-use pricing policies, while the "wind abandonment rate" and "light abandonment rate" of renewable energy can be reduced to improve the consumption level of renewable energy. On the other hand, energy storage power stations will not generate direct income, and the initial investment cost is considerable. To meet the requirements of peak regulation and energy storage quotas, wind power stations often choose to invest in energy storage power stations, but it is essential to make scientific investment decisions. When the capacity of the energy storage power stations is too small, it has no obvious effect on increasing renewable electricity consumption. However, the cost burden and resource waste will become more significant when the capacity is too large. Therefore, in the scientific investment decision-making of an energy storage power station, should we adopt a time-of-use pricing strategy or invest in an energy storage power station? What are the optimal energy storage capacity and electricity price? How do different incentive policies affect the capacity of energy storage stations? Which combination of strategies will result in lower carbon emissions? These are all fundamental issues that need to be considered and resolved when investing in energy storage power stations.

The main structure of this paper is as follows: Part 1 describes the research problem and explains the relevant functions and parameter symbols involved. Part 2 constructs a decision-making model under four strategies and obtains the corresponding optimal electricity price and optimal capacity of the energy storage power station. Part 3 analyzes the impact of key parameters on optimal decision-making and the effects of the two incentive policies are analyzed. Part 4 selects specific cases for numerical simulation analysis.

2. Literature review

Related to this topic, the research field includes renewable energy capacity investment, time-of-use pricing for electricity (also termed peak pricing, peak–valley pricing) and energy storage power stations. In terms of capacity investment, previous studies have focused mainly on the field of conventional energy (Crew *et al.*, 1995). However, due to the intermittency and low operating cost, renewable energy capacity investment research has gradually become a hot topic. On the one hand, the capacity investment decision is affected by the price fluctuation of renewable energy power and the electricity market environment. In the power generation market, price fluctuation is permitted, and fierce competition will lead to price surges and short-term demand fluctuations, affecting the equilibrium capacity (Tishler *et al.*, 2008). Higher price elasticity will discourage investment in renewable energy capacity (Kong *et al.*, 2019). Different electricity pricing policies affect renewable energy capacity (Kök *et al.*, 2018). Setting a reasonable purchase price or increasing penalties for power shortages can stimulate the capacity investment of renewable power (Xie *et al.*, 2018). The correlation between supply fluctuation and spot price fluctuation will affect the capacity investment scale of renewable energy (Kong *et al.*, 2017). On the other hand, the intermittency of renewable energy and the complementarity between different energy sources will also influence capacity investment. The impact of intermittency on investment in renewable energy capacity can be more clearly analyzed by setting the specific distribution of intermittency in renewable energy (Ambec and Crampes, 2012). Intermittency is critical in determining the optimal capacity mix between energy sources (Aflaki and Netessine, 2017). Data granularity for renewable yield and electricity demand is crucial; coarse data cannot accurately reflect intermittent renewable energy generation, which leads to excessive investment in renewable energy capacity (Hu *et al.*, 2015). Various studies have considered capacity investment as an exogenous parameter when describing the supply function equilibrium of the power spot market (Al-Gwaiz *et al.*, 2016; Sunar and Birge, 2019). Alternative location conditions will affect investment decisions on renewable energy (Xie *et al.*, 2017). Wind and flexible energy are complementary, and subsidies for flexible natural gas power plants will increase investment in wind energy (Kök *et al.*, 2020). When solar companies are restricted from leasing photovoltaic products, the installed capacity of renewable energy will be increased (Agrawal *et al.*, 2022). Existing studies provide references for the construction of an investment decision model in this paper. In contrast, this paper focuses on researching the capacity investment decisions of energy storage power stations that support existing wind power stations. In terms of model setting, it is close to Kök *et al.* (2018), with the following differences. On the one hand, this paper focuses on the influence of flat pricing and time-of-use pricing on the capacity investment of energy storage power stations supporting wind power stations, rather than the capacity investment decision of the wind power station itself. The energy storage power station's charge and discharge capacity is restricted by the power generation of wind power stations and the capacity of energy storage power stations simultaneously. On the other hand, considering the dual uncertainties of power supply and demand, the optimal capacity decision of energy storage power stations and its relationship with important parameters are analyzed.

Economists almost unanimously agree that time-of-use pricing (also known as peak pricing and peak–valley pricing) can improve the efficiency of the power system, reduce the cost of electricity (Kiguchi *et al.*, 2021), increase investment in distributed photovoltaic projects (Darghouth *et al.*, 2011) and reduce carbon emission levels (Holland and Mansur, 2008). The implementation of time-of-use pricing is intended to encourage electricity use at low prices during off-peak hours, thereby suppressing peak electricity demand (Catanzaro *et al.*, 2023). Some quantitative studies have found that under time-of-use pricing, customers will shift their power demand from peak to trough periods to reduce their electricity costs (Faruqui and Sergici, 2010), which tends to flatten peak demand (Hu *et al.*, 2018). However, it has also been found that total power demand remained unchanged across the two periods (Dong *et al.*, 2017). A robust optimization method can deal with the randomness of power demand (Hu *et al.*, 2018). The same pricing policy has different impacts on different types of renewable energy, and the pricing policy significantly impacts carbon emissions (Kök *et al.*, 2018). These studies use the difference in electricity prices to depict electricity consumption during peak and off-peak periods, which provides ideas for the setting of the demand function in this paper.

Regarding energy storage power stations, energy storage systems configured in a wind power station can significantly reduce the total expected cost and ease the intermittence of wind output (Qi *et al.*, 2015). A two-stage optimization method can be used to determine the optimal capacity of the distributed power station and the energy storage power station in a distributed generation–energy storage integration project (Li *et al.*, 2018). However, energy storage power stations face the bottleneck problem of high initial investment cost, which can be solved by utilizing energy storage subsidies, negative electricity prices and reasonable pricing mechanisms. Without government subsidies, existing energy storage power stations are not economically sustainable in the short term, while giving full play to the role of energy storage power stations in energy storage and price arbitrage provides a means of reducing subsidies for energy storage power stations (Locatelli *et al.*, 2015). A negative price can significantly change the optimal energy storage strategy structure (Zhou *et al.*, 2016). When selecting a pricing mechanism, coordinated bidding is the most valuable for pumped storage, and small facilities such as battery storage can choose intraday trading (Löhndorf and Wozabal, 2022). In the market of strategic cooperation between power generation and energy storage entities, compared with no energy storage, power generation enterprises' energy storage or cooperation with independent energy storage enterprises will reduce social welfare (Sioshansi, 2014). The supply and demand level of energy storage power stations is subject to the intermittency of wind power and fluctuations in power demand. Compared with previous studies, this paper focuses on the capacity investment decision-making of energy storage power stations under different power pricing policies when there is uncertainty in wind power supply and demand.

The literature review identified abundant research on renewable energy power capacity investment, time-of-use pricing, energy storage power stations and other aspects of operation management. However, more studies are needed on the capacity investment decisions of energy storage power stations under different pricing policies, especially relating to the dual uncertainty of power supply and demand. Unlike the capacity investment of renewable energy, the capacity investment of energy storage power stations is also subject to the intermittency of renewable energy, power demand fluctuations and the capacity of the power stations. However, the new idea of peak shaving that integrates a time-of-use pricing strategy and energy storage power stations is crucial to renewable energy power consumption and even carbon neutrality in the energy industry. Therefore, this paper takes wind power as an example, applies the model design idea of time-of-use pricing to the capacity investment decision model of energy storage power stations, and considers the influence of wind power intermittency and random fluctuations of peak power demand on the capacity investment decision of energy storage power stations, to provide a reference for the investment decisions of energy storage power stations supporting wind power projects. The study found that: (1) Investment in energy storage power stations under the same pricing method can always obtain higher profits, and the profits of power generators under different pricing methods are affected by parameter values. Time-of-use pricing reduces the optimal capacity of energy storage power stations. (2) The optimal capacity of the energy storage power station and the optimal electricity price are related to the intermittent wind resources, the unit investment cost of the energy storage power station, the price sensitivity of demand, the proportion of time-of-use pricing and other factors. (3) Investment in energy storage power stations under the same pricing method can reduce carbon emissions. Incentive policies can increase the scale of investment in energy storage power stations and reduce the level of carbon emissions in the supply chain.

3. Research question definition

3.1 Problem description

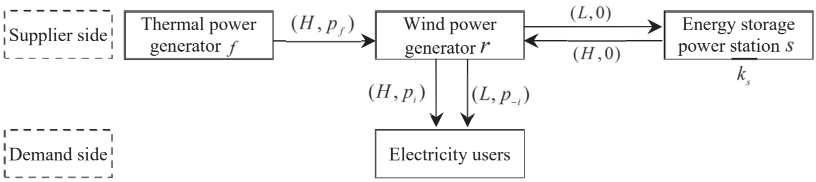
The intermittency of wind resources has led to fluctuations in wind power generation, and the scale of wind resources during troughs in demand is often more significant than that of during peak in demand (Faruqui and Sergici, 2010). The peak period of electricity demand is greater than the low period, resulting in a misalignment between wind power supply and peak demand. When operating wind power generation projects, the wind power generator needs to adjust peaks by configuring energy storage power stations and purchasing thermal power to meet the power needs of users. This paper constructs a two-stage wind power supply chain to study the energy storage power station investment decisions of the wind power generator. Electricity is supplied by a wind power generator (responsible for the investment and operation of wind power generation projects, investment in energy storage power stations and all electricity sales), energy storage power stations (subordinate departments of the wind power generator and responsible only for the daily operation and maintenance of energy storage power stations) and a thermal power generator (responsible for selling thermal power to the wind power generator for peak shaving). The demand side is all kinds of electricity users. In this case, the wind power generator is the main power supply body, while energy storage power stations and thermal power generators provide only wind power peak shaving auxiliary services.

Drawing on the literature (Kök *et al.*, 2018), a representative day in the project operation cycle is selected and divided into two periods: for simplified expression, the peak demand period is called daytime and the trough period of demand is called night. Combining the characteristics of wind power generation and electricity demand, the wind power generation capacity during the low period is greater than the electricity demand. Once the power generation capacity of the wind power generator has met the needs of the power users during the low period, the remaining electricity is supplied to the energy storage power station for storage. During peak periods, electricity demand is high, and wind power generation capacity cannot meet the needs of power users. Wind power generators require energy storage power stations to discharge and purchase from thermal power companies for peak regulation. Since the energy storage power station belongs to the wind power generator, there are significant upfront investment costs and extremely low daily operating and maintenance costs. Therefore, when there is a power shortage, the wind power generator prioritizes calling the energy storage power station to participate in peak shaving. Thermal power is purchased from thermal power suppliers (the purchase price is p_f) to make up for the shortfall. Wind power generators usually determine the electricity sale price p_i and the energy storage power station capacity k_s for wind power projects with determined capacity. Thermal power generators do not participate in decision-making, where p_f is an exogenous parameter. The relationship of each main structure is shown in Figure 1.

3.2 Function settings

Basic settings: Wind power projects (hereinafter referred to as wind power stations) and energy storage power stations have a long operating cycle. This paper considers only the electricity market conditions on a representative day of the operating cycle to reflect the overall situation. The day is divided into two phases, where $i \in \{H, L\}$: $i = H$ indicates the peak demand period, that is, daytime; and $i = L$ indicates a low demand period, that is, nighttime. We consider two pricing methods, expressed in terms of flat pricing and time-of-use pricing, where $j \in \{U, T\}$: $j = U$ indicates flat pricing and $j = T$ indicates time-of-use pricing.

Electricity price: Governments typically designate electricity prices as flat or time-of-use pricing, allowing the relevant power companies to negotiate a final tariff level (Faruqui and Sergici, 2010). p_i indicates the electricity sale price, where $p_i \geq 0$, $i \in \{H, L\}$. Under flat



Note(s): The first element in parentheses represents the period (H is the peak period, L is the low period), and the second element represents the electricity price
Source(s): Author's own creation

Figure 1. Wind power supply chain where energy storage power station participate in peak shaving

pricing, the electricity price is between that of the low and peak periods of time-of-use pricing. Under time-of-use pricing, the electricity price during the peak and low periods fluctuates up and down by a particular proportion, and there is a certain proportion of the relationship between the two [7]. Therefore, setting $p_L = \boldsymbol{\theta} p_H, \boldsymbol{\theta} \leq 1$ is the proportion of the electricity price during the low period to the electricity price during the peak period (when $\boldsymbol{\theta} = 1$ is the flat price; when $\boldsymbol{\theta} < 1$ is the time-of-use price, $\boldsymbol{\theta}$ is referred to as the proportion of time-of-use pricing). Referring to the provisions of "The Measures for the Administration of Electric Power Auxiliary Services" issued by China's National Energy Administration for the fixed compensation of thermal power and other participating auxiliary services, the price of thermal power for peak shaving p_f is set. When implementing flat pricing, to prevent an excessive rise in electricity prices, the government will set a catalog electricity price to limit the value range of electricity prices.

Demand function: Combining the demand survey data of power companies, the demand for electricity during peak periods is more volatile, while the demand in low periods is relatively stable, and the practice within the reference literature (Kök *et al.*, 2018) is to set demand from electricity users as a linear function of electricity prices. Price-sensitive electricity demand under time-of-use pricing will be delayed rather than disappear due to changes in electricity prices; for example, as some companies choose to produce at night to save electricity costs. For this reason, the peak period of electricity demand is $D_H(p_H) = A_H - \boldsymbol{\gamma} p_H + \boldsymbol{\gamma} p_L + \boldsymbol{\varepsilon} = A_H - \boldsymbol{\gamma}(1 - \boldsymbol{\theta}) p_H + \boldsymbol{\varepsilon}$, and the low period of electricity demand is $D_L(p_H) = A_L - \boldsymbol{\gamma} p_L + \boldsymbol{\gamma} p_H = A_L + \boldsymbol{\gamma}(1 - \boldsymbol{\theta}) p_H$. A_i is the scale of the electricity demand in period i, and by definition $A_H > A_L$. The own and cross-price sensitivities of the demand are set equal, denoted by $\boldsymbol{\gamma}$. $\boldsymbol{\varepsilon}$ is a random factor for peak power demand, followed by the distribution of the cumulative distribution function $F(x)$ and the probability density function $f(x)$, and the mean is zero, $\boldsymbol{\varepsilon} \in [-\boldsymbol{\alpha}_1, \boldsymbol{\alpha}_2]$. Energy storage power stations only provide peak shaving services for wind power, meaning the scale of energy storage power stations is much smaller than the daytime power demand, namely $k_s < D_H$, where the electricity demand and electricity market size units are both MWh.

Intermittent and power supply: u_i is set as the intermittent factor of wind power generation during period i. Drawing on the practice of the literature (Aflaki and Netessine, 2017), u_i is set as a random variable that follows the two-point distribution of 0–1, recorded as $u_i = [1, \boldsymbol{\rho}_i;\ 0, 1 - \boldsymbol{\rho}_i]$. This means that the probability of generating electricity according to the rated power of the indicated period is $\boldsymbol{\rho}_i$, and the probability of the wind power station not working is $1 - \boldsymbol{\rho}_i$. $\boldsymbol{\rho}_H$ is the daytime probability, and $\boldsymbol{\rho}_L$ is the nighttime probability. The wind power production function during peak and low periods is a linear function of $t_i u_i k_r$ with the linear function of wind power station capacity k_r, and where t_i is the duration of the i period. The unit is MWh.

Cost function: The cost of wind power stations and energy storage power stations comprises investment costs and operating costs. Based on the literature (Kök *et al.*, 2018) approach to the setting of investment costs, operating costs are a linear function of rated power. Since the unit operating cost is much lower than the unit investment cost, the former is converted into the latter. Given that both wind power stations and energy storage power stations have a life expectancy, the total unit investment cost during the operating cycle is converted into an average daily unit investment cost as the main cost of wind power stations and energy storage power stations. The daily investment cost function of a wind power station is $I_r(k_r) = \boldsymbol{\beta}_r k_r$, where k_r indicates the capacity of the wind power station and $\boldsymbol{\beta}_r$ represents the daily unit investment cost of the wind power station. The daily investment cost function of the energy storage power station is $I_s(k_s) = \boldsymbol{\beta}_s k_s$, where k_s indicates the scale of the energy storage power station and $\boldsymbol{\beta}_s$ indicates the daily unit investment cost of the energy storage power stations.

Carbon emissions: The carbon emission intensity of thermal power is set to 1; wind power generation and energy storage do not consume fuel, so the carbon emission is 0.

3.3 Parameter symbols

The parameter symbols used in this article are shown in Table 1.

3.4 Decision-making process

(1) Merit-order dispatch

During peak periods, the order of power supply is wind power, energy storage power station and thermal power. Wind power preferentially meets the demand for electricity during peak periods, with a maximum electricity supply of $\rho_H k_r$. When wind power cannot meet the electricity demand, the energy storage power station will make up the gap, with a maximum supply of k_s. If there is still unmet demand, the remaining shortfall will be satisfied by purchasing thermal power. The order of supply is shown in Figure 2(a).

(2) Timing of decisions

No investment in energy storage power stations: The wind power generator only determines the electricity price p_i when the capacity k_r of the wind power station is given.

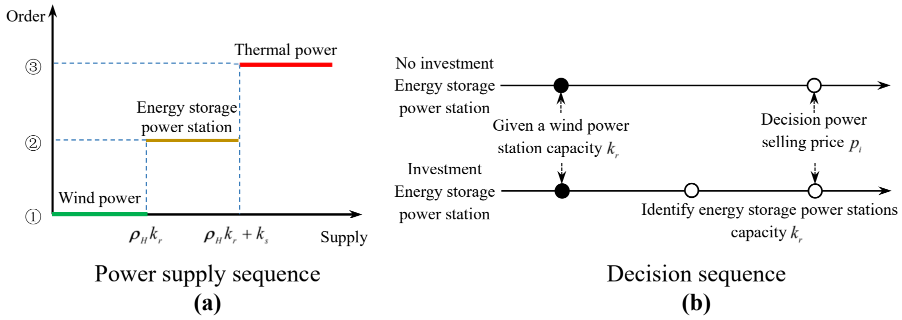
Investment in energy storage power stations: When given the capacity k_r of the wind power station, the wind power generator first determines the capacity of the energy storage power station that needs to be invested, and then sets the electricity price p_i, as shown in Figure 2(b).

To solve the problem of intermittent wind resources, the wind power generator can choose strategies such as time-of-use pricing or investment in energy storage power stations. A time-of-use pricing strategy can help in shifting some of the demand from peak periods to low periods (Kök *et al.*, 2018). Energy storage power stations can store excess electricity during the low period and use it to supply peak periods. Therefore, based on whether the wind power generator chooses time-of-use or flat pricing and invests in energy storage power stations,

Table 1. Variables and parameter notes

Symbol	Meaning	Symbol	Meaning
Model parameters			
p_f	Thermal power price for peak regulation	$\boldsymbol{\theta}$	the proportion of time-of-use pricing
$D_i(\cdot)$	Power demand function in period i	$\boldsymbol{\varepsilon}$	Random factor for electricity demand during peak period
A_i	Electricity market size in period i	$\boldsymbol{\alpha}_2, \boldsymbol{\alpha}_1$	Upper and lower limits of $\boldsymbol{\varepsilon}$
u_i	Intermittent factors in period i	$\boldsymbol{\gamma}$	Demand price sensitivity coefficient
$\boldsymbol{\beta}_r, \boldsymbol{\beta}_s$	The unit investment cost of a daily wind power station/energy storage power station	$\boldsymbol{\rho}_i$	Probability of $u_i = 1$ at a two-point distribution
$I_r(\cdot), I_s(\cdot)$	The total investment amount of a daily wind power station/energy storage power station	k_r	Wind power station capacity
$\boldsymbol{\pi}$	Profit function	t	The length of the i period, $t_H = t_L = t$
Superscript and subscript			
i	$i = H$ is a peak period, $i = L$ is a low period	r	Wind power generator
j	$j = U$ is flat pricing, $j = T$ is time-of-use pricing	s	Energy storage power station
*	Optimal decision-making	f	Thermal power generator
Decision variables			
k_s	Energy storage power station capacity	p_H	Electricity prices during peak period

Source(s): Author's own creation



Source(s): Author's own creation

Figure 2. Power supply sequence and decision sequence

four strategic combinations can be formed: UN (flat pricing, no investment in energy storage power stations), TN (time-of-use pricing, no investment in energy storage power stations), US (flat pricing, investment in energy storage power stations), TS (time-of-use pricing, investment in energy storage power stations). The wind power generator will then make optimal decisions for different combinations of strategies.

4. Optimal decision-making on wind power pricing

This section examines the basic model of solving pricing. It does not consider energy storage power station capacity investment.

4.1 Flat pricing decisions

Under the flat pricing strategy UN, the electricity price is equal throughout the day (noted as $p^{UN} = p_L^{UN} = p_H^{UN}$), corresponding to the proportion of time-of-use pricing $\boldsymbol{\theta} = 1$. Since there is no investment in energy storage power stations, the strategic wind power generator only determines the electricity price. The profit function of the wind power generator is

$$\max \boldsymbol{\pi}^{UN}\left(p^{UN}\right) = E\left[p^{UN} D_H\right] + p^{UN} D_L - p_f E\left[D_H - tu_H k_r\right]^+ - \boldsymbol{\beta}_r k_r \tag{1}$$

The first two items are the electricity sales revenue during the peak and low periods of the wind power generator, and the third is the cost of purchasing thermal power. The fourth is the investment cost of wind power stations. Equation (1) expands to obtain equation (2).

$$\max \boldsymbol{\pi}^{UN}\left(p^{UN}\right) = p^{UN}(A_H + A_L) - p_f A_H - p_f \boldsymbol{\rho}_H \left[\boldsymbol{\alpha}_2 - tk_r - \int_{tk_r - A_H}^{\boldsymbol{\alpha}_2} F(x)dx\right] - \boldsymbol{\beta}_r k_r \tag{2}$$

Proposal 1. Under the UN strategy, when choosing the national catalog electricity price cap for electricity sales, wind power generators can obtain the maximum profit.

According to formula (2) $\partial \boldsymbol{\pi}^{UN} / \partial p^{UN} = A_H + A_L > 0$, the wind power generator's profit is an increasing function concerning p^{UN}. Therefore, wind power generators can obtain the maximum profit at the upper limit of the electricity price.

Under this strategy, it is an oligopolistic market, and the electricity demand is not affected by the price of electricity. Wind power generators do not need to consider the loss of demand or demand transfer caused by excessively high electricity prices and focus on increasing the electricity price as much as possible to obtain higher profits. Excessively high electricity tariff levels will harm the interests of downstream power users. Therefore, under flat pricing, the government will establish an electricity price guidance catalog to limit the value range of electricity prices and prevent the emergence of excessive electricity prices. To obtain maximum profits, the wind power generator will choose the upper limit of the electricity price range to sell electricity.

Under the UN strategy, the carbon emissions level is

$$ECE^{UN} = E[A_H + \boldsymbol{\varepsilon} - tu_H k_r]^+ = \boldsymbol{\rho}_H(\boldsymbol{\alpha}_2 - tk_r) + A_H - \boldsymbol{\rho}_H \int_{tk_r - A_H}^{\boldsymbol{\alpha}_2} F(x)dx \tag{3}$$

Finding the first derivative of ECE^{UN} with respect to the daytime probability $\boldsymbol{\rho}_H$ for equation (3), we obtain property 1.

Property 1. Under the UN strategy, the level of carbon emissions decreases in daytime probability $\boldsymbol{\rho}_H$.

According to formula (3) $\partial ECE^{UN}/\partial\boldsymbol{\rho}_H = \boldsymbol{\alpha}_2 - tk_r - \int_{tk_r - A_H}^{\boldsymbol{\alpha}_2} F(x)dx$. Because the upper limit of daytime demand fluctuations $\boldsymbol{\alpha}_2$ is much smaller than that of wind power generation tk_r, we derive $\partial ECE^{UN}/\partial\boldsymbol{\rho}_H < 0$. When the daytime probability is high, this will reduce the daytime power gap caused by the intermittent wind power, and alleviate the imbalance between supply and demand. At this time, the amount of thermal power purchased by wind power generators for peak shaving will be correspondingly reduced, thereby reducing carbon emissions.

Corollary 1. In areas with abundant and stable wind resources, carbon emissions are relatively low.

4.2 Time-of-use pricing decisions

Under the TN strategy, the proportion of time-of-use pricing $\boldsymbol{\theta}$ is less than one. Similar to the UN strategy, the wind power generator only determines the electricity price. The profit function is

$$\max \boldsymbol{\pi}^{TN}\left(p_H^{TN}\right) = E\left[p_H^{TN} D_H\right] + \boldsymbol{\theta} p_H^{TN} D_L - p_f E[D_H - tu_H k_r]^+ - \boldsymbol{\beta}_r k_r \tag{4}$$

Under the TN strategy, the optimal electricity price is solved to obtain proposition 2 (Appendix 1).

Proposition 2. There is an optimal electricity price p_H^{TN*} under the TN strategy so that wind power generators can obtain maximum profits, and the optimal electricity price satisfies formula (5).

$$\boldsymbol{\gamma}(1-\boldsymbol{\theta})\left[p_f \boldsymbol{\rho}_H F\left(tk_r - A_H + \boldsymbol{\gamma}(1-\boldsymbol{\theta})p_H^{TN*}\right) + 2(1-\boldsymbol{\theta})p_H^{TN*}\right] = A_H + \boldsymbol{\theta} A_L + p_f \boldsymbol{\gamma}(1-\boldsymbol{\theta}) \tag{5}$$

Under time-of-use pricing, the difference in electricity prices in different periods will impact electricity demand. Higher peak electricity prices will cause peak electricity demand to shift to the low period, which will lead to a decrease in the overall electricity sales revenue. The transfer of electricity demand will reduce the gap between electricity supply and demand during peak periods, thereby saving the additional cost of purchasing thermal power. Wind power generators can therefore obtain maximum profits by adjusting the electricity price to balance the cost level between demand transfer and outsourced thermal power.

Property 2. Under the TN strategy, (1) the optimal electricity price p_H^{TN*} decreases in $\boldsymbol{\rho}_H$ and increases in p_f. (2) When $p_f\boldsymbol{\gamma} \le A_L$, p_H^{TN*} increases in the proportion of the time-of-use pricing $\boldsymbol{\theta}$. (3) When $0 \leq \boldsymbol{\theta} \leq 0.5$ and $p_H^{TN} \leq p_f \leq 2p_H^{TN}$, p_H^{TN*} decreases in the demand price sensitivity coefficient $\boldsymbol{\gamma}$ (Appendix 1).

Under the TN strategy, the higher probability of wind power generation in the peak period will reduce the gap between supply and demand, while the higher electricity price will lead to a transfer of electricity demand, which may jointly lead to insufficient demand during the peak period. This would lead to a reduction in total profit. A higher daytime probability is more appropriate for reducing the price of electricity. The increase in the peaking price of thermal power means that the cost of purchased thermal power for peak regulation increases. At this time, it is a better choice to guide the transfer of electricity demand through high electricity prices. The purpose of time-of-use pricing is to guide the transfer of demand to accomplish peak shaving by expanding the electricity price difference in different periods. An increase in the proportion of time-of-use pricing reduces the demand transfer rate. It is necessary to increase the electricity price to offset the excessively high cost of purchasing thermal power. When the proportion of time-of-use pricing does not exceed 0.5, the difference between electricity prices in different periods is not less than half of the electricity prices during the peak period. When the peaking price of thermal power sits between the peak-period electricity price and twice the peak-period electricity price, the increase in the demand price sensitivity coefficient will bring about rapid fluctuations in electricity demand. Only a reduction in the electricity price will curb the loss of profits caused by excessive demand shifting.

Under the TN strategy, the carbon emission level is $ECE^{TN} = E[A_H - \boldsymbol{\gamma}(1-\boldsymbol{\theta})p_H^{TN*} + \boldsymbol{\varepsilon} - tu_H \ k_r]^+$, and expansion gives $ECE^{TN} = \boldsymbol{\rho}_H(\boldsymbol{\alpha}_2 - tk_r) + A_H - \boldsymbol{\gamma}(1-\boldsymbol{\theta})p_H^{TN} - \boldsymbol{\rho}_H \int_{tk_r - A_H + \boldsymbol{\gamma}(1-\boldsymbol{\theta})p_H^{TN}}^{\boldsymbol{\alpha}_2} F(x)dx$.

Property 3. Under the TN strategy, (1) the level of carbon emissions decreases in $\boldsymbol{\gamma}$ and increases in $\boldsymbol{\theta}$; (2) the level of carbon emissions decreases in $\boldsymbol{\rho}_H$, and it decreases faster than under the UN strategy (Appendix 2).

The increase in the proportion of time-of-use pricing and the reduction in the demand price sensitivity coefficient will reduce the scale of power demand transfer from peak periods to low periods, thus reducing the effect of time-of-use pricing strategies to alleviate the imbalance between electricity supply and demand during peak periods. The supply–demand imbalance during peak periods is solved by increasing the amount of thermal power purchased, which increases the carbon emission level. At the same daytime probability level, due to the time-of-use pricing, some peak electricity demand will be transferred to the low period for consumption, which will reduce the amount of thermal power purchased for peak regulation to a certain extent to give a lower level of carbon emissions than under flat pricing.

Corollary 2. Given the same wind resource conditions, the carbon emission level of time-of-use pricing is lower than that of flat pricing.

5. Optimal decision-making for energy storage investment

5.1 Decision-making model for investing in energy storage power stations under flat pricing

Under the US strategy $\boldsymbol{\theta} = 1, p^{US} = p_L^{US} = p_H^{US}$. The wind power generator makes decisions on the electricity price and capacity of the energy storage power station. The wind power generator's profit function is

$$\max \boldsymbol{\pi}^{US}\left(k_s^{US}, p^{US}\right) = E\left[p^{US} D_H\right] + p^{US} D_L - p_f E\left[D_H - tu_H k_r - \min\left(\left(tu_L k_r - D_L\right)^+, k_s^{US}\right)\right]^+ - \boldsymbol{\beta}_r k_r - \boldsymbol{\beta}_s k_s^{US} \quad (6)$$

The first two items are the electricity sales revenue during the peak and low periods, and the third item is the cost of purchasing thermal power. The fourth and fifth items are the investment costs of wind power stations and energy storage power stations.

Under the US strategy, the optimal electricity price and energy storage power station capacity decisions are made, and proposition 3 is obtained (Appendix 3).

Proposition 3. Under the US strategy, the wind power generator can obtain the maximum profit when choosing the upper limit of the electricity price for electricity sales. When $\boldsymbol{\beta}_s \leq p_f \boldsymbol{\rho}_L$, the existence of the optimal energy storage power station capacity k_s^{US*} results in the maximum profit for the wind power generator. k_s^{US*} satisfies the following equation:

$$p_f \boldsymbol{\rho}_H \boldsymbol{\rho}_L F\left(tk_r + k_s^{US*} - A_H\right) = p_f \boldsymbol{\rho}_L - \boldsymbol{\beta}_s \tag{7}$$

Under this strategy, the optimal electricity price is similar to the UN strategy. Energy storage power stations have an obvious role in "peak shaving and valley filling." On the one hand, they store surplus electricity during the low period and reduce the waste of wind resources (that is, the problem of "curtailing wind"). On the other hand, they discharge during peak periods to enable peak shaving. Investment cost is the critical factor affecting the investment of energy storage power stations. If the unit investment cost is too high compared to the purchase of thermal power, there is no cost advantage to investing in energy storage power stations; instead, the better choice is for the wind power generator to purchase thermal power for peak regulation.

Corollary 3. When implementing a flat pricing strategy, the government must introduce measures such as electricity guidance prices to limit the maximum electricity price.

5.2 Decision-making model for investing in energy storage power stations under time-of-use pricing

Under the TS strategy $\boldsymbol{\theta} < 1$, electricity demand is affected by electricity prices. The wind power generator makes decisions on the electricity prices and capacity of energy storage power stations. The profit function of the wind power generator is

$$\begin{aligned} \max \boldsymbol{\pi}^{TS}\left(k_s^{TS}, p_H^{TS}\right) &= E\left[p_H^{TS} D_H\right] + \boldsymbol{\theta} p_H^{TS} D_L \\ &\quad - p_f E\left[D_H - tu_H k_r - \min\left((tu_L k_r - D_L)^+, k_s^{TS}\right)\right]^+ - \boldsymbol{\beta}_r k_r - \boldsymbol{\beta}_s k_s^{TS} \end{aligned} \tag{8}$$

The reverse order method solves the optimal electricity price and the optimal capacity of the energy storage power station. Proposition 4 (Appendix 4) is obtained.

Proposition 4. Under the TS strategy $\boldsymbol{\beta}_s \leq p_f \boldsymbol{\rho}_L$, there is the optimal electricity price p_H^{TS*} and the optimal capacity of the energy storage power station k_s^{TS*}, which means the wind power generator earns the maximum profit. p_H^{TS*}, k_s^{TS*} meets the following formula:

$$\begin{aligned} &\boldsymbol{\gamma}(1-\boldsymbol{\theta})\left[p_f \boldsymbol{\rho}_H (1-\boldsymbol{\rho}_L) F\left(tk_r + \boldsymbol{\gamma}(1-\boldsymbol{\theta}) p_H^{TS*} - A_H\right) + 2(1-\boldsymbol{\theta}) p_H^{TS*}\right] \\ &\quad = A_H(1+\boldsymbol{\theta}) + \boldsymbol{\gamma}(1-\boldsymbol{\theta})\left[p_f(1-\boldsymbol{\rho}_L) + \boldsymbol{\beta}_s\right] p_f \boldsymbol{\rho}_H \boldsymbol{\rho}_L F\left(tk_r + \boldsymbol{\gamma}(1-\boldsymbol{\theta}) p_H^{TS*} - A_H + k_s^{TS*}\right) \\ &\quad = p_f \boldsymbol{\rho}_L - \boldsymbol{\beta}_s \end{aligned} \tag{9}$$

Under this combination of strategies, wind power generators use time-of-use pricing and energy storage power stations to adjust peaks. Time-of-use electricity prices can promote the transfer of electricity demand during peak periods, and energy storage power stations can conduct peak shaving through "trough charging–peak discharge." When the unit investment cost of the energy storage power station offers a cost advantage over the peaking price of thermal power, there is an optimal capacity for energy storage power stations.

5.3 Analysis of the nature of optimal decision-making for investment in energy storage power stations

5.3.1 The impact of pricing methods on energy storage capacity decisions.

Property 4. When $\boldsymbol{\beta}_s \leq p_f \boldsymbol{\rho}_L$, the optimal capacity k_s^{US*} is larger than the optimal capacity k_s^{TS*}; that is, time-of-use pricing reduces the optimal capacity of energy storage power stations. The decreasing margin $\Delta k_s^* = k_s^{US*} - k_s^{TS*}$ increases in $\boldsymbol{\gamma}$ and decreases in $\boldsymbol{\theta}$.

Due to the $p_f, \boldsymbol{\rho}_H, \boldsymbol{\rho}_L, \boldsymbol{\beta}_s$ numeric values are not affected by the pricing method. According to Equations (5) and (7), we can obtain $F(tk_r + k_s^{US*} - A_H) = F(tk_r + \boldsymbol{\gamma}(1-\boldsymbol{\theta})p_H^{TS*} - A_H + k_s^{TS*})$. The distribution function $F(x)$ is a monotonic increment function. Therefore, $tk_r + k_s^{US*} - A_H = tk_r + \boldsymbol{\gamma}(1-\boldsymbol{\theta})p_H^{TS*} - A_H + k_s^{TS*}$ produces $\Delta k_s^* = k_s^{US*} - k_s^{TS*} = \boldsymbol{\gamma}(1-\boldsymbol{\theta}) p_H^{TS*} > 0$. Meanwhile, we proved $\partial \Delta k_s^* / \partial \boldsymbol{\gamma} = (1-\boldsymbol{\theta})p_H^{TS*} > 0$, $\partial \Delta k_s^* / \partial \boldsymbol{\theta} = -\boldsymbol{\gamma} p_H^{TS*} < 0$.

Since electricity demand is affected by the electricity sale price, under time-of-use pricing, there is a difference in electricity prices between the peak and low periods, which will lead to the transfer of electricity demand during the peak period of electricity users to save electricity bills. That is, time-of-use pricing will reduce the demand during the peak electricity consumption period and increase the demand during the low electricity consumption period. The power generation surplus during the peak and low periods thus declines and the capacity demand for corresponding energy storage power stations decreases, while the opposite occurs under flat pricing. The greater the demand price sensitivity coefficient, the larger the scale of demand transfer for the same electricity price level. The smaller the proportion of time-of-use pricing, the greater the price difference between peak and low valley electricity, and the larger the scale of demand transfer under the same demand price sensitivity coefficient, the greater the reduction in the capacity of the corresponding optimal energy storage power station.

Corollary 4. During periods or in regions with sharp variations between electricity supply and demand (such as winter and summer, areas with large temperature differences between day and night), time-of-use pricing strategies are conducive to alleviating the imbalance between power supply and demand during peak periods. Time-of-use pricing is appropriate for use in regions with abundant wind resources and limited funds to reduce the capacity of energy storage power stations.

5.3.2 Analysis of the impact of energy storage investment on optimal decision-making.

Property 5. The unit investment cost of energy storage power stations $\boldsymbol{\beta}_s$ is affected by the combination of p_f and $\boldsymbol{\rho}_L$, and there is an upper limit $p_f \boldsymbol{\rho}_L$.

The investment cost is the most important cost element within the investment and operation of energy storage power stations. When wind power generators pursue profit maximization as their business goal, the premise of investing in energy storage power stations is that their unit investment cost should be lower than, or even much lower than, the cost of regulating peaks via the purchase of thermal power that considers the nighttime probability. Specifically, the wind power generator purchases thermal power for peak demand shaving, and there is no excessive procurement. Investing in energy storage power stations as internal facilities to support peak shaving for wind power stations carries the risk of an insufficient utilization rate (that is, excess capacity), and the utilization rate of energy storage power stations is mainly affected by the nighttime probability. In the cost calculation, the investment cost of the unused part of the energy storage power station capacity must also be apportioned. Therefore, the upper limit of the unit investment cost of energy storage power stations cannot be higher than the product of the peaking price of thermal power and nighttime probability as opposed to the peaking price of thermal power. Otherwise, the unit investment cost of energy storage power stations is too high, and the investment presents no cost advantage compared with purchasing thermal power for peak regulation. In this case, the optimal decision of wind power generators is not to invest in the construction of energy storage power stations.

Corollary 5. To promote the rapid development of energy storage power stations, enterprises should be encouraged to increase energy storage technology innovation or government investment subsidies for energy storage power stations to reduce unit investment costs and enhance cost advantages.

Property 6. The optimal capacity of the energy storage power station k_s^{jS*} decreases in $\boldsymbol{\beta}_s$ and capacity of the wind power station k_r. Optimal electricity prices under time-of-use pricing p_H^{TS*} increase in $\boldsymbol{\beta}_s$ and k_r (Appendix 5).

The unit investment cost is one of the most critical factors restricting the development of energy storage power stations. Higher unit investment costs will reduce the capacity of energy storage power stations, thereby weakening their peak regulation capacity. It is necessary to increase the peak price to expand demand transfer for peak regulation. The greater the capacity of the wind power station, the stronger the power supply capacity during peak periods, and the more the gap between supply and demand will be reduced, which will correspondingly reduce the capacity of the energy storage power station and the optimal electricity price.

5.3.3 Analysis of the impact of wind power intermittentness on optimal decision-making.

Property 7. k_s^{jS*} decreases in $\boldsymbol{\rho}_H$ and increases in $\boldsymbol{\rho}_L$ (Appendix 6).

The intermittency of wind resources is one of the most important reasons for the discrepancy between electricity supply and demand during peak periods, and the probability of power generation determines the efficiency of wind power generation. In the case of relatively stable power demand during the low period, the increase in nighttime probability will lead to an increase in the surplus of wind power, thereby increasing the amount of electricity supplied to the energy storage power station for charging and indirectly reducing the peak price of electricity. An increase in the daytime probability will increase the amount of daytime wind power generation. At the same level of electricity demand, the power gap during peak periods will decrease, thereby reducing the demand for discharge peak regulation of energy storage power stations. Therefore, abundant and stable wind resources can play a role in peak shaving and valley filling.

Corollary 6. In areas with abundant and stable wind resources, the capacity of supporting energy storage power stations can be moderately reduced, and power can be sold using flat pricing. In areas where wind resources are not abundant or sufficiently stable, it is necessary to moderately increase the capacity of supporting energy storage power stations and employ time-of-use pricing for power sales.

The carbon emission levels of the US and TS strategies are as follows:

$$
\begin{aligned}
ECE^{US} &= \boldsymbol{\rho}_H(\boldsymbol{\alpha}_2 - tk_r) + A_H - \boldsymbol{\rho}_L k_s^{US} - \boldsymbol{\rho}_H \left[\boldsymbol{\rho}_L \int_{tk_r + k_s^{US} - A_H}^{\boldsymbol{\alpha}_2} F(x)dx \right. \\
&\quad \left. + (1 - \boldsymbol{\rho}_L) \int_{tk_r - A_H}^{\boldsymbol{\alpha}_2} F(x)dx \right] \\
ECE^{TS} &= \boldsymbol{\rho}_H(\boldsymbol{\alpha}_2 - tk_r) + A_H - \boldsymbol{\gamma}(1 - \boldsymbol{\theta})p_H^{TS} - \boldsymbol{\rho}_L k_s^{TS} - \boldsymbol{\rho}_H \left[\boldsymbol{\rho}_L \int_{G + k_s^{TS}}^{\boldsymbol{\alpha}_2} F(x)dx \right. \\
&\quad \left. + (1 - \boldsymbol{\rho}_L) \int_{G}^{\boldsymbol{\alpha}_2} F(x)dx \right]
\end{aligned}
\tag{10}
$$

Therefore, it has the following properties.

Property 8. (1) Under the US and TS strategies, the carbon emission level decreases in $\boldsymbol{\rho}_H$ and $\boldsymbol{\rho}_L$. (2) Under the TS strategy, as $\boldsymbol{\rho}_H$ increases, the carbon emission level decreases faster than under the other three strategies (Appendix 7).

The higher daytime probability will reduce the daytime power gap caused by intermittent wind power and alleviate the imbalance between supply and demand to a certain extent. The higher nighttime probability will increase the optimal energy storage power station scale, thereby increasing the power supply of the energy storage power station to peak periods. Therefore, higher daytime and nighttime probabilities will reduce the amount of thermal power purchased by wind turbines for peak shaving and reduce the level of carbon emissions.

Although carbon emission levels are affected by daytime probability, the degree of influence varies under different strategies. Under the TS strategy, due to the simultaneous shift of daytime demand to nighttime and the partial replacement of thermal power by energy storage power stations, the carbon emission level is less affected by the daytime probability under this strategy than under the other three strategies.

Corollary 7. In areas where wind resources are not abundant or are unstable, time-of-use pricing and investment in energy storage power plant strategy can achieve the lowest carbon emission levels.

5.3.4 The influence of electricity price-related parameters on optimal decision-making. The relevant parameters of electricity price mainly involve the demand price sensitivity coefficient $\boldsymbol{\gamma}$, the proportion of time-of-use pricing $\boldsymbol{\theta}$ and the thermal power price for peak regulation p_f. The analysis is as follows:

Property 9. (1) k_s^{jS*} increases in p_f. Under the TS strategy, k_s^{TS*} decreases in $\boldsymbol{\gamma}$ and increases in $\boldsymbol{\theta}$. (2) For time-of-use pricing, the optimal electricity price p_H^{TS*} increases in p_f. When $0 \leq \boldsymbol{\theta} \leq 0.5$ and $p_H^{TN} \leq p_f \leq 2p_H^{TN}$, p_H^{TS*} decreases in $\boldsymbol{\gamma}$. When $\boldsymbol{\gamma} p_f \leq A_L$, p_H^{TS*} increases in $\boldsymbol{\theta}$.

Time-of-use pricing, energy storage power stations and purchased thermal power have an alternative relationship in peak regulation, and the increase in the thermal power price for peak regulation will reduce the competitiveness of thermal power peak regulation and will promote an increase in energy storage power station capacity or electricity prices during peak periods. An increase in the demand price sensitivity coefficient or a decrease in the proportion of time-of-use pricing will increase the scale of power demand transfer during peak periods, corresponding to a reduction in the optimal capacity of energy storage power stations and electricity prices during peak periods.

Corollary 8. In areas where demand is highly sensitive to electricity prices, there is a large difference between electricity prices during peak and low periods, meaning electricity prices during peak periods or energy storage power station capacity can be appropriately reduced.

Property 10. Under the TS strategy, (1) carbon emission levels increase in $\boldsymbol{\theta}$, and the growth rate is lower than the TN strategy. (2) Carbon emission levels decrease in $\boldsymbol{\gamma}$, and the rate of reduction is greater than that of the TN strategy (Appendix 9).

An increase in the proportion of time-of-use pricing and a reduction of the demand price sensitivity coefficient will weaken the effect of time-of-use pricing strategies in alleviating the imbalance between electricity supply and demand during peak periods, increasing carbon emission levels. From property 9, it can be seen that the increase in the proportion of time-of-use pricing and the reduction of the demand price sensitivity coefficient under the TS strategy will increase the investment scale of optimal energy storage power stations, further increase the scale of energy storage power stations to replace purchased thermal power and then slow down the growth rate of carbon emission levels.

Corollary 9. When implementing a time-of-use pricing strategy, investing in energy storage power stations significantly reduces carbon emissions.

5.4 The policy effect of investing in energy storage power stations under time-of-use pricing

To promote the development of energy storage power stations, the government will introduce positive-incentive (such as electricity subsidies for energy storage power stations according to discharge) or negative-incentive (such as carbon constraints, referred to as carbon fees) policies. To study the effects of different incentive policies, the amount of electricity subsidies for energy storage power stations is set as v (unit is yuan/MWh, $v \geq 0, v = 0$ indicating that no subsidies are paid), the unit carbon emission cost is c ($c \geq 0, c = 0$, indicating that no carbon fee is charged), and the carbon emission cost will be transferred to the wind power generator through trading.

This section focuses on the effect of incentive policies on promoting the development of energy storage power stations, so only the optimal energy storage power station capacity is determined. When considering both positive and negative incentives under the TS strategy, it is called the TSP strategy, and the corresponding profit function of the wind power generator is

$$\begin{aligned} \max \boldsymbol{\pi}^{TSP}\left(k_s^{TSP}\right) &= E[p_H D_H] + \boldsymbol{\theta} p_H D_L \\ &\quad - (p_f + c)E\left[D_H - tu_H k_r - \min\left((tu_L k_r - D_L)^+, k_s^{TSP}\right)\right]^+ \\ &\quad + vE\left[\min\left((tu_L k_r - D_L)^+, k_s^{TSP}\right)\right]^+ - \boldsymbol{\beta}_r k_r - \boldsymbol{\beta}_s k_s^{TSP} \end{aligned} \tag{11}$$

The optimal capacity decision of the energy storage power station is made under the TSP strategy, and proposition 5 is obtained (Appendix 10).

Proposition 5. When $\boldsymbol{\theta} < 1$ and $\boldsymbol{\beta}_s \leq (p_f + c + v)\boldsymbol{\rho}_L$, the optimal capacity k_s^{TSP*} exists for energy storage power stations under the TSP strategy so that wind power generators can obtain maximum profits, and k_s^{TSP*} satisfies the following equation:

$$(p_f + c)\boldsymbol{\rho}_H \boldsymbol{\rho}_L F\left(tk_r + \boldsymbol{\gamma}(1 - \boldsymbol{\theta})p_H - A_H + k_s^{TSP*}\right) = (p_f + c)\boldsymbol{\rho}_L - \boldsymbol{\beta}_s + v\boldsymbol{\rho}_L \tag{12}$$

Property 11. When there is a subsidy or carbon fee policy, the optimal capacity k_s^{TSP*} for energy storage power stations is improved compared to under the TS strategy (namely $k_s^{TSP*} > k_s^{TS*}$). At the same time, there is an increase in the amount of electricity subsidy v and carbon emission costs c (Appendix 10).

Comparing propositions 4 and 5, the unit investment costs for energy storage power stations under the TSP strategy are reduced compared to the TS strategy. Whether through subsidizing electricity or implementing a carbon fees policy, the TSP strategy has played a role in indirectly reducing unit investment costs and enhancing cost-competitive advantages. That is, with the same unit investment cost, positive or negative incentives can promote the development of energy storage power stations.

Corollary 10. In the early stage of energy storage power station development, rapid progress can be promoted through policies such as subsidies for energy storage power stations or the levying of carbon fees on thermal power.

Under the TSP strategy, the level of carbon emissions is

$$ECE^{TSP} = E\left[A_H - \boldsymbol{\gamma}(1-\boldsymbol{\theta})p_H + \boldsymbol{\varepsilon} - tu_H k_r - \min\left((tu_L k_r - D_L)^+, k_s^{TSP}\right)\right]^+ \tag{13}$$

Property 12. Under the TSP strategy, (1) The level of carbon emissions decreases in $\boldsymbol{\rho}_H, \boldsymbol{\rho}_L$ and $\boldsymbol{\gamma}$ and increases in $\boldsymbol{\theta}$. (2) The level of carbon emissions under the TSP strategy is lower than under the TS strategy (Appendix 10).

From property 11, it is evident that the investment scale of energy storage power stations under the TSP strategy is greater than that of the TS strategy, and under the same conditions, the scale of thermal power purchased for peak shaving by energy storage power stations under the TSP strategy is higher than that of the TS strategy, thereby reducing the carbon emission level.

Corollary 11. When there is an incentive policy for energy storage power stations, carbon emissions will be reduced.

6. Numerical analysis

6.1 Case parameter settings

Taking a wind power station energy storage project of the Datang Group as an example, the project is located in Long'an District, Anyang City, Henan Province, with a total investment of 5.09 million yuan in the energy storage system. The other parameter settings are shown in Table 2.

The parameters are set according to the following: (1) Based on the 20-year service life of core equipment such as wind turbines, wind power towers and main transformers, the life cycle of the wind power station is determined to be 20 years, corresponding to the unit investment cost of the wind power station per day. (2) Regarding the relevant requirements of Guangxi and Shanxi Province, it is determined that the energy storage power station is circulated 5,000 times during its life cycle, and is cycled once a day, corresponding to the unit investment cost of the energy storage power station per day [8]. (3) According to the Notice of the National Development and Reform Commission on Further Improving the Time-of-use Electricity Price Mechanism and the specific practices of Jiangsu Province, the electricity price in market transactions is determined to be 550 yuan/MWh (under flat pricing), while the peak and low prices fluctuate up and down in a certain proportion, respectively. (4) In line

Table 2.
Parameter values

Parameter	Parameter symbols	Parameter value	Data sources
Wind power station capacity(MW)	k_r	30	known
The unit investment cost of a daily wind power station (Yuan/MW)	β_r	1,150	Based on(1)
The unit investment cost of a daily energy storage power station(Yuan/MWh)	β_s	220	Based on(2)
Daytime/Nighttime probability	ρ_H / ρ_L	0.3/0.33	Kök *et al.* (2018)
Electricity prices under flat pricing(Yuan/MWh)	p^U	550	Based on (3)
Peak electricity prices under time-of-use pricing(Yuan/MWh)	p_H^T	660	Based on (3)
The proportion of time-of-use pricing	θ	0.75	Based on (3)
Thermal power price for peak regulation (Yuan/MWh)	p_f	1,000	Based on (4)
Electricity market size in peak/low period (MW)	A_H / A_L	365/350	Based on (5)
Demand price sensitivity coefficient	γ	0.02	Based on (5)
Upper and lower limits of ε	α_2/α_1	10/3	Based on (5)
The length of each period	t	12	

Source(s): The values of daytime and nighttime probabilities are estimated based on literature (Kök *et al.*, 2018) Other values are calculated by the author based on publicly available data, and the calculation instructions are detailed in “6.1 Case parameter settings”

with practices in northeast and northwest China, the electricity price for thermal power participating in peak shaving auxiliary services is set at 1,000 yuan/MWh [9]. (5) Combined studies (Kök *et al.*, 2018; Tishler *et al.*, 2008) and the scale of the case project are converted to obtain the values for the electricity market size, the demand price sensitivity coefficient and the upper and lower limits of the demand stochastic factor.

Electricity demand is a key factor in investment decisions in energy storage power stations. A specific distribution is given to the random demand factor to explore the impact of demand uncertainty on investment. Drawing on the practice of Tishler *et al.* (2008), the random demand factor is set to follow a uniform distribution, and the corresponding distribution function and the parameter values in Table 2 are substituted into formulas (1)–(10). The expressions for wind power station profit, optimal capacity of energy storage power station and optimal electricity price can then be obtained as a basis for numerical analysis.

6.2 Profit-based optimal decision-making choice for wind power generator

6.2.1 Demand price sensitivity coefficient and the proportion of time-of-use pricing. Given the demand price sensitivity coefficient $\gamma \in [0, 0.04]$ and the proportion of time-of-use pricing $\theta \in [0.4, 1]$, the optimal decision-making choices of the wind power generator under the pricing strategy and energy storage power station investment strategy are studied, respectively.

(1) Under the same pricing strategy, through numerical simulation analysis, in the optimal decision distribution graph, compared with the UN strategy, the US strategy is always the optimal decision. Similarly, the TS strategy is always the optimal decision compared to the TN strategy. That is, under the same pricing strategy, within the range of values for the given demand price elasticity and the proportion of time-of-use pricing, the optimal decision for wind power generators is to invest in energy storage power stations.

(2) For the same energy storage power station investment strategy, the four strategies are divided into two groups according to whether to invest in energy storage power

stations. As can be seen from Figure 3, the demand price sensitivity coefficient has a small impact on the profits of wind power generators. When the proportion of time-of-use pricing $\boldsymbol{\theta}$ is small, as in area I of Figure 3(a) and 3(b), a higher profit can be obtained using flat pricing; conversely, the profit is higher under time-of-use pricing.

When implementing time-of-use pricing, the proportion should not be too low ($\boldsymbol{\theta} \geq 0.66$); that is, the difference between the price of electricity during the peak and low periods should not be too large. Otherwise, the excessive demand transfer will offset the cost savings realized by the reduction in thermal power purchased and may even lead to a decrease in profits.

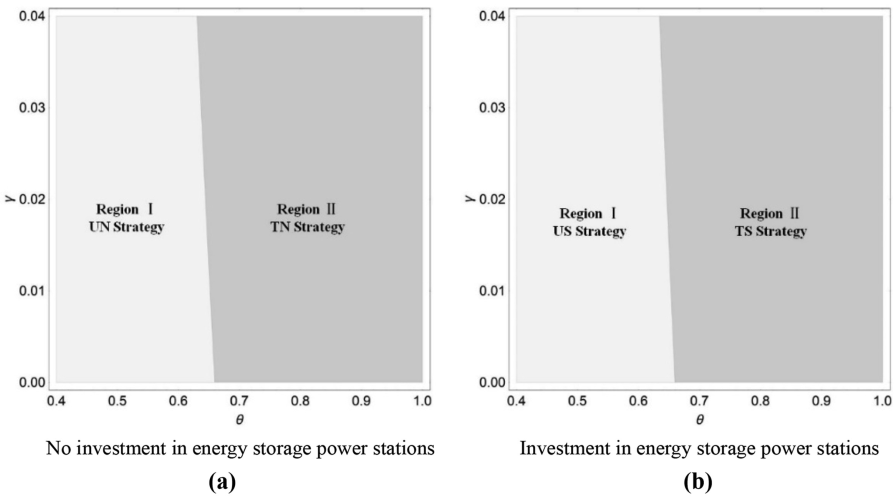
In summary, regarding the investment decision for the same energy storage power station, the optimal decision of wind power generators is subject to the proportion of time-of-use pricing $\boldsymbol{\theta}$. Thus, when $\boldsymbol{\theta}$ is relatively small, they should select a flat pricing strategy (UN strategy, US strategy); when $\boldsymbol{\theta}$ is relatively large, they should select a time-of-use pricing strategy (TN strategy, TS strategy).

Corollary 12. When implementing time-of-use pricing, the difference between the electricity price during the peak and low periods should not be too large.

6.2.2 Energy storage investment and incentive policies.

(1) Impact of the unit investment cost of energy storage power stations

The unit investment cost of energy storage power stations is set at $\boldsymbol{\beta}_s \in [170, 270]$. As can be seen from Figure 4(a), the profits of wind power generators under time-of-use pricing are much higher than those under flat pricing. When investing in energy storage power stations, the increase $\boldsymbol{\beta}_s$ will reduce the profits of wind power generators, but the impact is limited. Taking $\boldsymbol{\beta}_s = 220$ as an example, the profit difference between the two strategies under the same pricing method does not exceed 1,030 yuan. The minimum profit difference between the different pricing methods is 22,652 yuan, which is much greater than the former. Based on the above analysis, within the range of the unit investment cost of a given energy storage power station, the TS strategy is the optimal decision for wind power generators.



Source(s): Author's own creation by applying Mathematica 12.1 software

Figure 3. The impact of electricity price elasticity and the proportion of time-of-use pricing on profit

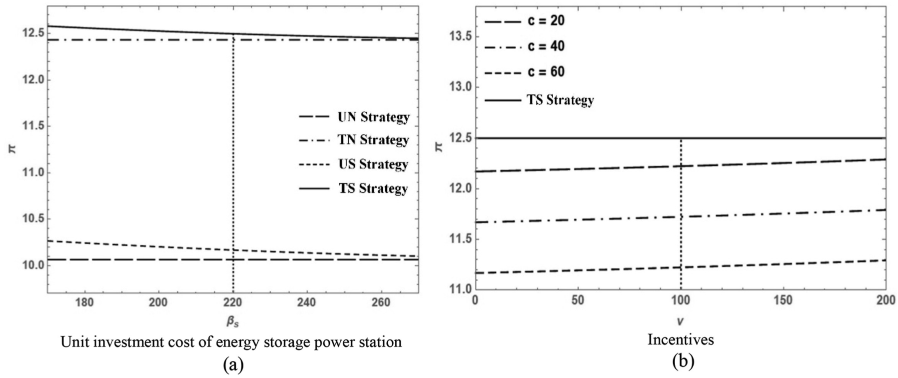


Figure 4.
The impact of energy storage investment and incentive policies on profits

Source(s): Author's own creation by applying Mathematica 12.1 software

(2) Analysis of the impact of incentive policies

Taking the practice of Qinghai and other provinces, the electricity subsidy for energy storage power stations is set at $v \in [0, 200]$. Referring to the transaction data of The Shenzhen Carbon Emission Spot Trading System, the unit carbon emission costs are set at $c = 20$, $c = 40$ and $c = 60$. From Figure 4(b), it can be seen that the profit of wind power generators increases in v. However, the low growth rate is associated with a small proportion of subsidy income. With different carbon emission costs, the profits of wind power generators decrease in c, and the decline rate is obvious. When there is an incentive policy, the total profit of wind power generators is always lower than under the TS strategy; that is, the income obtained by wind power generators from the subsidy for energy storage power stations is always less than the increase in carbon emission costs caused by the purchase of thermal power for peak regulation.

Corollary 13. When determining a standard carbon fee for thermal power in the auxiliary service market, it is necessary to balance the relationship between the wind power generators' loss of revenue and the growth of investment in energy storage power stations.

6.3 Optimal decision-making based on carbon emission levels

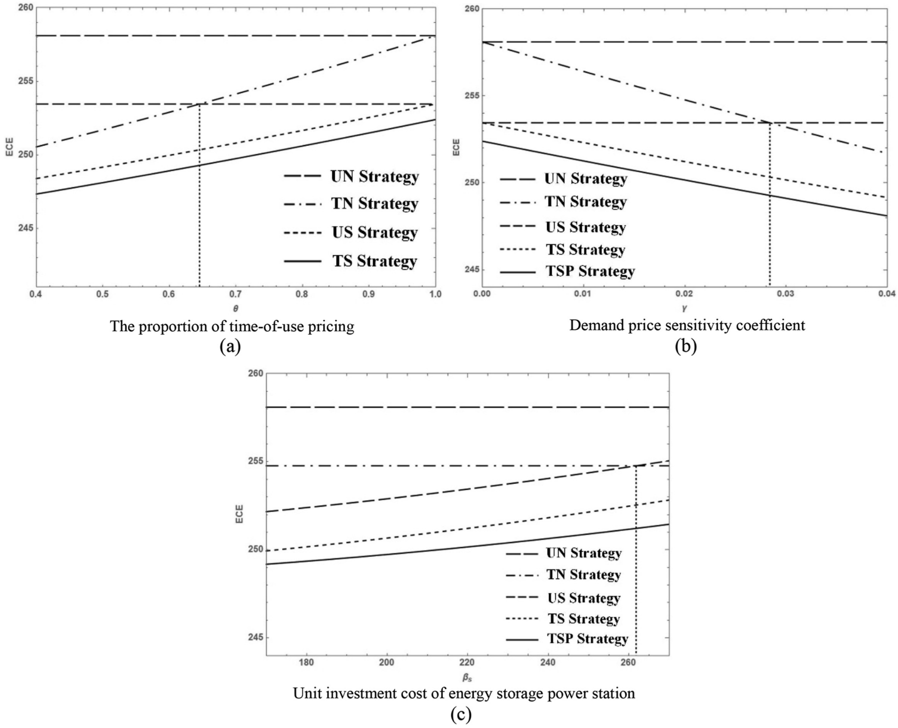
Given a random requirement factor following a uniform distribution, the expected carbon emission expression under the four strategies can be obtained. To further investigate the influencing factors affecting the level of carbon emissions under the different strategies, we performed numerical simulations for critical parameters.

(1) The proportion of time-of-use pricing

As shown in Figure 5(a), given the proportion of time-of-use pricing $\boldsymbol{\theta} \in [0.4, 1]$, carbon emissions under flat pricing are fixed and under time-of-use pricing increase in $\boldsymbol{\theta}$. Given the same pricing method, the carbon emissions of investing in energy storage power stations are always low. When the proportion of time-of-use pricing is relatively low ($\boldsymbol{\theta} \leq 0.6451$), carbon emissions under the TN strategy are lower than those in the US strategy. The opposite is true when the proportion is larger.

(2) Demand price sensitivity coefficient

As shown in Figure 5(b), given the demand price sensitivity coefficient, carbon emissions under flat pricing are fixed and decrease in $\boldsymbol{\gamma}$ under time-of-use pricing. Given the same



Source(s): Author's own creation by applying Mathematica 12.1 software

Figure 5. The impact of different factors on carbon emissions

pricing method, the carbon emissions of investing in energy storage power stations are always lower. When the demand price sensitivity coefficient is large (i.e., $\gamma \geq 0.0284$), carbon emissions are lower in the TN strategy than in the US strategy, and the opposite is true when it is smaller. The TSP strategy has the lowest carbon emissions.

(3) Unit investment cost of energy storage power station

As shown in Figure 5(c), given the unit investment cost of an energy storage power station $\beta_s \in [170, 270]$, the carbon emissions of non-investment in energy storage power stations are fixed, while those of both strategies for investing in energy storage power stations (the US strategy and TS strategy) increase in β_s. Given the same pricing method, carbon emissions under the strategy of investing in energy storage power stations are always lower. When the unit investment cost is high (i.e., $\beta_s \geq 261.76$), carbon emissions are higher in the US strategy compared to the TN strategy, and the opposite is true when it is low. The TSP strategy has the lowest level of carbon emissions.

In summary, from the perspective of carbon emissions reduction, investing in energy storage power stations under time-of-use pricing is the optimal decision for wind power generators.

Corollary 14. Time-of-use pricing, investment in energy storage power stations, or incentive policies can effectively reduce carbon emissions.

7. Conclusion and future research

7.1 Research conclusion

Energy restructuring is critical to achieving carbon neutrality targets, and with the rapid growth of installed wind power capacity with zero carbon emissions, demand is increasing for peak shaving services. Time-of-use pricing and energy storage power stations are effective means of solving the problem of peak regulation of wind power stations. Investment in energy storage power stations is affected by both investment costs and factors such as intermittent wind resources, pricing methods, fluctuations in power demand and peaking electricity prices. Therefore, studying the impact of energy storage power station capacity, time-of-use electricity price and incentive policies on the profits and carbon emissions of wind power generators reveals the interrelationships between the optimal capacity of energy storage power stations, the optimal electricity price and other factors. It can provide a reference for the pricing and energy storage power station investment decisions of wind power stations and the introduction and implementation of relevant government incentive policies. This study has made several findings. First, concerning the optimal decision-making aspect, under flat pricing, the optimal electricity price is the upper limit of the price. Under time-of-use pricing, there is an optimal electricity price that maximizes the profit of wind power generators. When the unit investment cost of the energy storage power station is lower than the peaking price of thermal power that considers nighttime probability, the energy storage power station has an optimal capacity that maximizes the profit of the wind power generator in both pricing methods. The optimal capacity of energy storage power stations under time-of-use pricing is lower than under flat pricing, and the difference between the two increases in the demand price sensitivity coefficient and decreases in the proportion of time-of-use pricing. The second finding concerns the optimal decision-making choice. Under the same pricing method, investment in energy storage power stations is the optimal decision, and the optimal decision of the wind power generator under time-of-use pricing is affected by the value of the relevant parameters of the electricity price. Within the range of the unit investment cost of a given energy storage power station and considering the level of carbon emissions, the TS strategy is optimal for wind power generators. The study's third finding concerns the interrelationships between the decision-making variables and influencing factors. When the level of demand transfer induced by the thermal power price is not higher than that of the low electricity demand period, and its value is between the peak-period electricity price and twice the peak-period electricity price, the optimal electricity price increases in the proportion of the time-of-use pricing and decreases in demand price elasticity, and the optimal capacity of energy storage power station properties are similar. The optimal capacity of the energy storage power station shows a monotonically decreasing relationship with daytime probability and an increasing relationship with nighttime probability. The optimal electricity price has a decreasing relationship with both the daytime and nighttime probability. The optimal capacity of an energy storage power station decreases in the capacity of the wind power station, while the unit investment cost of the energy storage power station and the optimal electricity price decrease in the capacity of the wind power station and increase in the unit investment cost of the energy storage power station. There is a substitution relationship between time-of-use pricing, energy storage power stations and purchased thermal power, while an increase in the cost of thermal power for peak regulation will increase the optimal electricity price and the optimal capacity of energy storage power stations. The fourth finding involves policy effects and carbon emissions. When there is a subsidy or carbon fee policy, the optimal capacity of the energy storage power station is greater than under the TS strategy. Such a policy leads to an increase in the amount of electricity subsidies and the cost of carbon emissions. The level of carbon emissions is affected by the intermittency of wind resources, the demand price sensitivity coefficient and the proportion of time-of-use pricing. Investment in energy storage power stations can reduce the impact of carbon emissions. Carbon emissions are always reduced when incentives exist.

7.2 Policy suggestions

The following suggestions are made to increase the enthusiasm of wind power generators to invest in energy storage power stations:

First, upstream and downstream enterprises should actively cooperate to promote technological innovation in energy storage equipment to reduce energy storage investment costs.

Since an energy storage power station does not directly generate income and the initial investment cost is large, the high unit investment cost will seriously diminish the enthusiasm of wind power generators for energy storage investment. As such, full play should be given to the respective advantages of upstream and downstream enterprises, and joint technological research should be conducted on key energy storage equipment to continuously improve the performance of energy storage equipment and reduce the unit investment cost of energy storage.

Second, real-time monitoring should be conducted of wind resources through the Internet of Things, big data and other technologies to support scientific investment decisions.

The intermittency of wind resources is an important factor affecting the capacity demand of energy storage power stations. Failure to accurately master or predict the intermittency level will lead to a particular deviation between the capacity investment decision of the energy storage power station and the actual demand, resulting in wasted or under-invested investments. With the help of sensors, mobile communication, big data and other technologies, real-time monitoring of wind speed and other key indicators can be used to scientifically predict the intermittency of wind resources in the future and provide a basis for scientific investment decisions.

Third, in the early stage of development, subsidies and tax incentives can be adopted to support the accelerated installation of energy storage power stations.

In the early stage of development, due to the limited technical level, production process and other factors, the purchase cost of the core equipment for an energy storage power station is too high, which will directly increase the investment cost of wind power generators. At this time, incentive policies such as project subsidies, energy storage kilowatt-hour subsidies and tax breaks should be actively introduced to ease the cost pressure of energy storage investment and encourage wind power generators to actively deploy energy storage power stations.

Fourth, we should coordinate the implementation of time-of-use pricing, energy storage investment and incentive policies to reduce the comprehensive cost of wind power consumption.

Incentive policies help to improve the investment scale of energy storage power stations, and the increase in peak–valley price difference will reduce the capacity demand of energy storage power stations. However, improper operation poses the risk of incentive policies transferring investment costs to the government, while excessive peak-to-valley price differentials will lead to "peak–valley inversion." Therefore, time-of-use pricing, energy storage investment and incentive policies should be implemented in line with the regional reality, to reduce the comprehensive cost as far as possible while ensuring the consumption of wind power.

7.3 Future research

In this paper, the research idea of time-of-use pricing was introduced into the investment decisions of energy storage power stations in the context of intermittent wind power supply and random fluctuations in demand to study the capacity decisions of energy storage power stations. It can provide ideas for the investment research of energy storage power stations under different situations. In future research, the concept may be expanded around the themes of the uncertain capacity of wind power stations and energy storage power stations, independent investment and pricing mechanisms for energy storage power stations. In addition, the pricing mechanism of multi-class energy storage facilities on the demand side has significant research value.

Notes

1. https://m.gmw.cn/baijia/2021-08/04/1302459174.html
2. https://www.iea.org/reports/global-energy-review-2021
3. http://www.nea.gov.cn/2022-01/26/c_1310441589.htm; http://zfxxgk.nea.gov.cn/auto87/201704/t20170418_2773.htm
4. http://www.xinhuanet.com/power/2017-11/24/c_1122004857.htm
5. http://www.gov.cn/zhengce/zhengceku/2021-07/24/content_5627088.htm
6. http://www.chinapower.com.cn/qingneng/dongtai/20210202/49789.html
7. https://www.ndrc.gov.cn/xwdt/tzgg/202107/t20210729_1292068.html?code=&state=123
8. http://sxsnyj.shanxi.gov.cn/POLICY/cxwj/aiY7fa.htm; https://newenergy.in-en.com/html/newenergy-2405660.shtml
9. https://guangfu.bjx.com.cn/news/20190116/956991.shtml; https://www.doc88.com/p-30929040666211.html

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(The Appendix follows overleaf)

Appendix 1

(1) Proof of Proposition 2

Equation (4) is expanded to obtain Equation A1

$$\max \boldsymbol{\pi}^{TN}\left(p_H^{TN}\right) = -(1-\boldsymbol{\theta})^2\boldsymbol{\gamma}\left(p_H^{TN}\right)^2 + \left[A_H + \boldsymbol{\theta}A_L + p_f\boldsymbol{\gamma}(1-\boldsymbol{\theta})\right]p_H^{TN} - p_f\boldsymbol{\rho}_H\left[\boldsymbol{\alpha}_2 - tk_r - \int_{tk_r - A_H + \boldsymbol{\gamma}(1-\boldsymbol{\theta})p_H^{TN}}^{\boldsymbol{\alpha}_2} F(x)dx\right] - p_f A_H - \boldsymbol{\beta}_r k_r \tag{A1}$$

Find the first derivative and second derivative of the profit function in equation A1 on the electricity price p_H^{TN}, and obtain equation A2 and A3, respectively

$$\frac{\partial \boldsymbol{\pi}^{TN}\left(p_H^{TN}\right)}{\partial p_H^{TN}} = -2(1-\boldsymbol{\theta})^2\boldsymbol{\gamma}p_H^{TN} + A_H + \boldsymbol{\theta}A_L + p_f\boldsymbol{\gamma}(1-\boldsymbol{\theta}) - p_f\boldsymbol{\rho}_H\boldsymbol{\gamma}(1-\boldsymbol{\theta})F\left(tk_r - A_H + \boldsymbol{\gamma}(1-\boldsymbol{\theta})p_H^{TN}\right) \tag{A2}$$

$$\frac{\partial^2 \boldsymbol{\pi}^{TN}\left(p_H^{TN}\right)}{\partial \left(p_H^{TN}\right)^2} = -2(1-\boldsymbol{\theta})^2\boldsymbol{\gamma} - p_f\boldsymbol{\rho}_H\boldsymbol{\gamma}^2(1-\boldsymbol{\theta})^2 f\left(tk_r - A_H + \boldsymbol{\gamma}(1-\boldsymbol{\theta})p_H^{TN}\right) < 0 \tag{A3}$$

Because $\boldsymbol{\theta} < 1$ and $f(tk_r + k_s - A_H) > 0$, get $\partial^2\boldsymbol{\pi}^{TN}(p_H^{TN})/\partial(p_H^{TN})^2 < 0$, implies the profit function of wind power generator is the concave function of electricity price p_H^{TN}.

According to the first-order condition (FOC), let the first derivative equal 0 to obtain the expression of the optimal electricity price p_H^{TN*}, as shown in Equation (5).

(2) Proof of property 2

The partial derivatives of the $\boldsymbol{\theta}, \boldsymbol{\gamma}, \boldsymbol{\rho}_H, p_f$ are found on each side of equation A2, get

$$\frac{\partial^2 \boldsymbol{\pi}^{TN}\left(p_H^{TN}\right)}{\partial p_H^{TN}\partial \boldsymbol{\theta}} = 4(1-\boldsymbol{\theta})\boldsymbol{\gamma}p_H^{TN} + A_L - p_f\boldsymbol{\gamma} + p_f\boldsymbol{\rho}_H\boldsymbol{\gamma}F\left(tk_r - A_H + \boldsymbol{\gamma}(1-\boldsymbol{\theta})p_H^{TN}\right) + p_f p_H^{TN}\boldsymbol{\rho}_H\boldsymbol{\gamma}^2(1-\boldsymbol{\theta})f\left(tk_r - A_H + \boldsymbol{\gamma}(1-\boldsymbol{\theta})p_H^{TN}\right)$$

$$\frac{\partial^2 \boldsymbol{\pi}^{TN}\left(p_H^{TN}\right)}{\partial p_H^{TN}\partial r} = -(1-\boldsymbol{\theta})\left[2(1-\boldsymbol{\theta})p_H^{TN} - p_f\right] - p_f\boldsymbol{\rho}_H(1-\boldsymbol{\theta})F\left(tk_r - A_H + \boldsymbol{\gamma}(1-\boldsymbol{\theta})p_H^{TN}\right) - p_f p_H^{TN}\boldsymbol{\rho}_H\boldsymbol{\gamma}(1-\boldsymbol{\theta})^2 f\left(tk_r - A_H + \boldsymbol{\gamma}(1-\boldsymbol{\theta})p_H^{TN}\right)$$

$$\frac{\partial^2 \boldsymbol{\pi}^{TN}\left(p_H^{TN}\right)}{\partial p_H^{TN}\partial \boldsymbol{\rho}_H} = -p_f\boldsymbol{\gamma}(1-\boldsymbol{\theta})F\left(tk_r - A_H + \boldsymbol{\gamma}(1-\boldsymbol{\theta})p_H^{TN}\right) < 0$$

$$\frac{\partial^2 \boldsymbol{\pi}^{TN}\left(p_H^{TN}\right)}{\partial p_H^{TN}\partial p_f} = \boldsymbol{\gamma}(1-\boldsymbol{\theta})\left[1 - \boldsymbol{\rho}_H F\left(tk_r - A_H + \boldsymbol{\gamma}(1-\boldsymbol{\theta})p_H^{TN}\right)\right] > 0$$

When $p_f\boldsymbol{\gamma} \le A_L$, get $\frac{\partial^2\boldsymbol{\pi}^{TN}(p_H^{TN})}{\partial p_H^{TN}\partial\boldsymbol{\theta}} > 0$. When $p_f \le 2(1-\boldsymbol{\theta})p_H^{TN}$ and $p_f \ge p_H^{TN}$, we can get $\boldsymbol{\theta} \le 0.5$. When $0 \le \boldsymbol{\theta} \le 0.5$ and $p_H^{TN} \le p_f \le 2p_H^{TN}$, the corresponding is $\frac{\partial^2\boldsymbol{\pi}^{TN}(p_H^{TN})}{\partial p_H^{TN}\partial\boldsymbol{\gamma}} < 0$.

By proposition 2, it can be obtained $\frac{\partial}{\partial p_H^{TN}}\left(\frac{\boldsymbol{\pi}^{TN}(p_H^{TN})}{p_H^{TN}}\right) < 0$. Under the corresponding conditions, it can be obtained $\partial p_H^{TN}/\partial\boldsymbol{\theta} > 0$, $\partial p_H^{TN}/\partial\boldsymbol{\gamma} < 0$, $\partial p_H^{TN}/\partial\boldsymbol{\rho}_H < 0$, $\partial p_H^{TN}/\partial p_f > 0$.

Appendix 2

Proof of property 3.

Under the TN strategy, we find the first derivative of the carbon emission level ECE^{TN} with respect to $\boldsymbol{\rho}_H$, $\boldsymbol{\theta}$, $\boldsymbol{\gamma}$, respectively.

$$\frac{\partial ECE^{TN}}{\partial\boldsymbol{\rho}_H} = \boldsymbol{\alpha}_2 - tk_r - \int_{tk_r-A_H+\boldsymbol{\gamma}(1-\boldsymbol{\theta})p_H^{TN}}^{\boldsymbol{\alpha}_2} F(x)dx, \frac{\partial ECE^{TN}}{\partial\boldsymbol{\theta}}$$

$$= \boldsymbol{\gamma} p_H^{TN}\left[1 - \boldsymbol{\rho}_H F\left(tk_r - A_H + \boldsymbol{\gamma}(1-\boldsymbol{\theta})p_H^{TN}\right)\right]$$

$$\frac{\partial ECE^{TN}}{\partial\boldsymbol{\gamma}} = (1-\boldsymbol{\theta})p_H^{TN}\left[\boldsymbol{\rho}_H F\left(tk_r - A_H + \boldsymbol{\gamma}(1-\boldsymbol{\theta})p_H^{TN}\right) - 1\right]$$

By the property 1 to prove the process and the range of values of each parameter, easy to obtain $\partial ECE^{TN}/\partial\boldsymbol{\rho}_H < 0$, $\partial ECE^{TN}/\partial\boldsymbol{\theta} > 0$, $\partial ECE^{TN}/\partial\boldsymbol{\gamma} < 0$.

$$\frac{\partial ECE^{TN}}{\partial\boldsymbol{\rho}_H} - \frac{\partial ECE^{UN}}{\partial\boldsymbol{\rho}_H} = \int_{tk_r-A_H}^{\boldsymbol{\alpha}_2} F(x)dx - \int_{tk_r-A_H+\boldsymbol{\gamma}(1-\boldsymbol{\theta})p_H^{TN}}^{\boldsymbol{\alpha}_2} F(x)dx$$

$$= \int_{tk_r-A_H}^{tk_r-A_H+\boldsymbol{\gamma}(1-\boldsymbol{\theta})p_H^{TN}} F(x)dx > 0, \text{property 3 proven}$$

Appendix 3

Proof of Proposition 3.

Equation (6) is expanded to obtain Equation A4

$$\max \boldsymbol{\pi}^{US}\left(k_s^{US}, p^{US}\right) = (A_H + A_L)p^{US} - p_f\left[\boldsymbol{\rho}_H(\boldsymbol{\alpha}_2 - tk_r) + A_H - \boldsymbol{\rho}_L k_s^{US}\right] + p_f\boldsymbol{\rho}_H\boldsymbol{\rho}_L\int_{tk_r+k_s^{US}-A_H}^{\boldsymbol{\alpha}_2} F(x)dx + p_f\boldsymbol{\rho}_H(1-\boldsymbol{\rho}_L)\int_{tk_r-A_H}^{\boldsymbol{\alpha}_2} F(x)dx - \boldsymbol{\beta}_r k_r - \boldsymbol{\beta}_s k_s^{US} \tag{A4}$$

The first derivative of the profit function in Equation A4 on the electricity price p_H^{US} can be obtained $\partial\boldsymbol{\pi}^{US}(k_s^{US}, p^{US})/\partial p^{US} = A_H + A_L$. The profit function of the is a monotonous incremental function of the electricity price, so the wind power generator can obtain the maximum profit at the upper limit of the electricity price.

The first and second derivatives of the profit function in Equation A4 regarding the capacity of the energy storage power station k_s^{US} are respectively

$$\frac{\partial\boldsymbol{\pi}^{US}\left(k_s^{US}, p^{US}\right)}{\partial k_s^{US}} = p_f\boldsymbol{\rho}_L - \boldsymbol{\beta}_s - p_f\boldsymbol{\rho}_H\boldsymbol{\rho}_L F\left(tk_r + k_s^{US} - A_H\right),$$

$$\frac{\partial^2\boldsymbol{\pi}^{US}\left(k_s^{US}, p^{US}\right)}{\partial\left(k_s^{US}\right)^2} = -p_f\boldsymbol{\rho}_H\boldsymbol{\rho}_L f\left(tk_r + k_s^{US} - A_H\right)$$

As $f(tk_r + k_s - A_H) > 0$, we can see $\partial^2 \boldsymbol{\pi}^{US}(k_s^{US}, p^{US})/\partial(k_s^{US})^2 < 0$. The profit of wind power generator is a concave function of the capacity of energy storage power station. According to the first-order condition (FOC), let the first derivative equal 0 to obtain the expression of the optimal capacity of energy storage power station when $\boldsymbol{\beta}_s \le p_f \boldsymbol{\rho}_L$. It is shown as Equation (7). We get property 3.

Appendix 4

Proof of Proposition 4.

Equation (8) is expanded to obtain Equation A5

$$\max \boldsymbol{\pi}^{TS}\left(k_s^{TS}, p_H^{TS}\right) = -(1-\boldsymbol{\theta})^2 \boldsymbol{\gamma}\left(p_H^{TS}\right)^2 + (A_H + \boldsymbol{\theta} A_L) p_H^{TS} - p_f \Big[A_H - \boldsymbol{\gamma}(1-\boldsymbol{\theta}) p_H^{TS} + \boldsymbol{\rho}_H(\boldsymbol{\alpha}_2 - tk_r) - \boldsymbol{\rho}_L k_s^{TS}\Big] + p_f \boldsymbol{\rho}_H \left[\boldsymbol{\rho}_L \int_{G+k_s^{TS}}^{\boldsymbol{\alpha}_2} F(x)dx + (1-\boldsymbol{\rho}_L)\int_G^{\boldsymbol{\alpha}_2} F(x)dx\right] - \boldsymbol{\beta}_r k_r - \boldsymbol{\beta}_s k_s^{TS} \tag{A5}$$

Among which, $G = tk_r + \boldsymbol{\gamma}(1-\boldsymbol{\theta}) p_H^{TS} - A_H$.

Solve by reverse order:

Step 1: Find the optimal electricity price. Separately find the first derivative and second derivative of the profit function in Equation (A5) with respect to the electricity price p_H^{TS} respectively, as follows

$$\frac{\partial \boldsymbol{\pi}^{TS}\left(k_s^{TS}, p_H^{TS}\right)}{\partial p_H^{TS}} = -2(1-\boldsymbol{\theta})^2 \boldsymbol{\gamma} p_H^{TS} + A_H + \boldsymbol{\theta} A_L + p_f \boldsymbol{\gamma}(1-\boldsymbol{\theta}) - p_f \boldsymbol{\rho}_H \boldsymbol{\gamma}(1-\boldsymbol{\theta})\left[\boldsymbol{\rho}_L F\left(G + k_s^{TS}\right) + (1-\boldsymbol{\rho}_L)F(G)\right]$$

$$\frac{\partial^2 \boldsymbol{\pi}^{TS}\left(k_s^{TS}, p_H^{TS}\right)}{\partial \left(p_H^{TS}\right)^2} = -2(1-\boldsymbol{\theta})^2 \boldsymbol{\gamma} - p_f \boldsymbol{\rho}_H \boldsymbol{\gamma}^2 (1-\boldsymbol{\theta})^2 \left[\boldsymbol{\rho}_L f\left(G + k_s^{TS}\right) + (1-\boldsymbol{\rho}_L) f(G)\right] \tag{A6}$$

When $\boldsymbol{\theta} < 1$, easy to get $\partial^2 \boldsymbol{\pi}^{TS}(k_s^{TS}, p_H^{TS})/\partial(p_H^{TS})^2 < 0$. The profit function is about the price's concave function. There is an optimal price p_H^{TS*} that allows the profit function to be maximized. According to the first-order condition FOC, let the first derivative equal 0 to get equation A7.

$$p_f \boldsymbol{\rho}_H \boldsymbol{\gamma}(1-\boldsymbol{\theta})\left[\boldsymbol{\rho}_L F\left(G + k_s^{TS*}\right) + (1-\boldsymbol{\rho}_L)F(G)\right] + 2(1-\boldsymbol{\theta})^2 \boldsymbol{\gamma} p_H^{TS*} = A_H + \boldsymbol{\theta} A_L + p_f \boldsymbol{\gamma}(1-\boldsymbol{\theta}) \tag{A7}$$

Step 2: Find the optimal energy storage power station capacity. Find the first derivative and the second derivative of the profit function with respect to the capacity of the energy storage power station k_s^{TS}, respectively, as follows

$$\begin{aligned} \frac{\partial \boldsymbol{\pi}^{TS}\left(k_s^{TS}, p_H^{TS}\right)}{\partial k_s^{TS}} &= p_f \boldsymbol{\rho}_L - \boldsymbol{\beta}_s - p_f \boldsymbol{\rho}_H \boldsymbol{\rho}_L F\left(G + k_s^{TS}\right), \\ \frac{\partial^2 \boldsymbol{\pi}^{TS}\left(k_s^{TS}, p_H^{TS}\right)}{\partial \left(k_s^{TS}\right)^2} &= -p_f \boldsymbol{\rho}_H \boldsymbol{\rho}_L f\left(G + k_s^{TS}\right) < 0, \end{aligned} \tag{A8}$$

Easy to get $\partial^2\boldsymbol{\pi}^{TS}(k_s^{TS}, p_H^{TS})/\partial(k_s^{TS})^2 < 0$, so the profit function is a concave function of the capacity of the energy storage station. There is an optimal energy storage power station capacity k_s^{TS*} that maximizes wind power generator profits. According to the FOC, when $\boldsymbol{\beta}_s \leq p_f\boldsymbol{\rho}_L$, getting Equation A9:

$$p_f\boldsymbol{\rho}_H\boldsymbol{\rho}_L F\left(tk_r + \boldsymbol{\gamma}(1-\boldsymbol{\theta})p_H^{TS*} - A_H + k_s^{TS*}\right) = p_f\boldsymbol{\rho}_L - \boldsymbol{\beta}_s \tag{A9}$$

In conjunction with A7 and A9, gets equation (9). And property 3 can be obtained.

Appendix 5

Proof of property 6.

(1) Flat pricing

We find the first derivative of k_s^{US*} with respect to k_r, $\boldsymbol{\beta}_s$ for both sides of Equation (7), get $f(tk_r + k_s^{US*} - A_H)\left(t + \frac{\partial k_s^{US*}}{\partial k_r}\right) = 0$, $f(tk_r + k_s^{US*} - A_H)\frac{\partial k_s^{US*}}{\partial \boldsymbol{\beta}_s} = -\frac{\boldsymbol{\beta}_s}{p_f\boldsymbol{\rho}_H\boldsymbol{\rho}_L}$, easy to get $\partial k_s^{US*}/\partial k_r < 0$, $\partial k_s^{US*}/\partial\boldsymbol{\beta}_s < 0$.

(2) Time-of-use pricing

We find the first derivative of p_H^{TS*} with respect to $\boldsymbol{\beta}_s$ for the first expression of Equation (9). Namely $\frac{\partial p_H^{TS*}}{\partial\boldsymbol{\beta}_s}[p_f\boldsymbol{\rho}_H(1-\boldsymbol{\rho}_L)\boldsymbol{\gamma}(1-\boldsymbol{\theta})f(G) + 2(1-\boldsymbol{\theta})] = 1$ and $p_f\boldsymbol{\rho}_H(1-\boldsymbol{\rho}_L)\boldsymbol{\gamma}(1-\boldsymbol{\theta})f(G) + 2(1-\boldsymbol{\theta}) > 0$, get $\partial p_H^{TS*}/\ \partial\boldsymbol{\beta}_s > 0$.

Find the partial derivative of k_r for Equation A6 and $k_r, \boldsymbol{\beta}_s$ for Equation A8, respectively. As follows:

$$\frac{\partial^2\boldsymbol{\pi}^{TS}\left(k_s^{TS}, p_H^{TS}\right)}{\partial p_H^{TS}\partial k_r} = -tp_f\boldsymbol{\rho}_H\boldsymbol{\gamma}(1-\boldsymbol{\theta})\left[\boldsymbol{\rho}_L f\left(G + k_s^{TS}\right) + (1-\boldsymbol{\rho}_L)f(G)\right] < 0$$

$$\frac{\partial^2\boldsymbol{\pi}^{TS}\left(k_s^{TS}, p_H^{TS}\right)}{\partial k_s^{TS}\partial k_r} = -tp_f\boldsymbol{\rho}_H\boldsymbol{\rho}_L f\left(G + k_s^{TS}\right) < 0, \frac{\partial^2\boldsymbol{\pi}^{TS}\left(k_s^{TS}, p_H^{TS}\right)}{\partial k_s^{TS}\partial\boldsymbol{\beta}_s} = -1 < 0$$

This is known by proposition 3 and 4, $\frac{\partial}{\partial k_s^{TS}}\left(\frac{\partial\boldsymbol{\pi}^{TS}(k_s^{TS}, p_H^{TS})}{\partial k_s^{TS}}\right) < 0$, $\frac{\partial}{\partial p_H^{TS}}\left(\frac{\partial\boldsymbol{\pi}^{TS}(k_s^{TS}, p_H^{TS})}{\partial p_H^{TS}}\right) < 0$. So, $\partial p_H^{TS*}/\partial k_r < 0$, $\partial k_s^{TS*}/\partial k_r < 0$, $\partial k_s^{TS*}/\partial\boldsymbol{\beta}_s < 0$, proof.

Appendix 6

Proof of property 7.

(1) Flat pricing

We find the first derivative of k_s^{US*} with respect to $\boldsymbol{\rho}_H, \boldsymbol{\rho}_L$ for both sides of Equation (7), get

$$f\left(tk_r + k_s^{US*} - A_H\right)\frac{\partial k_s^{US*}}{\partial\boldsymbol{\rho}_H} = -\left(1 - \frac{\boldsymbol{\beta}_s}{p_f\boldsymbol{\rho}_L}\right)\frac{1}{\boldsymbol{\rho}_H^2}, f\left(tk_r + k_s^{US*} - A_H\right)$$

$$\frac{\partial k_s^{US*}}{\partial\boldsymbol{\rho}_L} = \frac{\boldsymbol{\beta}_s}{p_f\boldsymbol{\rho}_H\boldsymbol{\rho}_L^2}, \text{easy to get } \partial k_s^{US*}\Big/\partial\boldsymbol{\rho}_H < 0, \partial k_s^{US*}\Big/\partial\boldsymbol{\rho}_L > 0.$$

(2) Time-of-use pricing

Find the partial derivative of $\boldsymbol{\rho}_H$ and $\boldsymbol{\rho}_L$ for Equation A6 and A8, respectively. As follows:

$$\frac{\partial^2\boldsymbol{\pi}^{TS}\left(k_s^{TS}, p_H^{TS}\right)}{\partial p_H^{TS}\partial\boldsymbol{\rho}_H} = -p_f\boldsymbol{\gamma}(1-\boldsymbol{\theta})\left[\boldsymbol{\rho}_L F\left(G + k_s^{TS}\right) + (1-\boldsymbol{\rho}_L)F(G)\right] < 0$$

$$\frac{\partial^2 \boldsymbol{\pi}^{TS}\left(k_s^{TS}, p_H^{TS}\right)}{\partial p_H^{TS} \partial \boldsymbol{\rho}_L} = -p_f \boldsymbol{\rho}_H \boldsymbol{\gamma}(1-\boldsymbol{\theta})\left[F\left(G+k_s^{TS}\right) - F(G)\right] < 0$$

$$\frac{\partial^2 \boldsymbol{\pi}^{TS}\left(k_s^{TS}, p_H^{TS}\right)}{\partial k_s^{TS} \partial \boldsymbol{\rho}_H} = -p_f \boldsymbol{\rho}_L F\left(G+k_s^{TS}\right) < 0 \quad \frac{\partial^2 \boldsymbol{\pi}^{TS}\left(k_s^{TS}, p_H^{TS}\right)}{\partial k_s^{TS} \partial \boldsymbol{\rho}_L} = p_f\left[1-\boldsymbol{\rho}_H F\left(G+k_s^{TS}\right)\right] > 0$$

Easy to get $\partial k_s^{TS*}/\partial \boldsymbol{\rho}_H < 0$, $\partial k_s^{TS*}/\partial \boldsymbol{\rho}_L > 0$, $\partial p_H^{TS*}/\partial \boldsymbol{\rho}_H < 0$, $\partial p_H^{TS*}/\partial \boldsymbol{\rho}_L < 0$, proof.

Appendix 7

Proof of property 8(1).

Under the US strategy and TS strategy, find the first derivative of ECE^{US} and ECE^{TS} with respect to $\boldsymbol{\rho}_H, \boldsymbol{\rho}_L$ for both sides of Equation (10).

$$\frac{\partial ECE^{US}}{\partial \boldsymbol{\rho}_H} = \boldsymbol{\alpha}_2 - tk_r - \boldsymbol{\rho}_L \int_{tk_r+k_s^{US}-A_H}^{\boldsymbol{\alpha}_2} F(x)dx - (1-\boldsymbol{\rho}_L)\int_{tk_r-A_H}^{\boldsymbol{\alpha}_2} F(x)dx$$

$$\frac{\partial ECE^{US}}{\partial \boldsymbol{\rho}_L} = -k_s^{US} - \boldsymbol{\rho}_H\left[\int_{tk_r+k_s^{US}-A_H}^{\boldsymbol{\alpha}_2} F(x)dx - \int_{tk_r-A_H}^{\boldsymbol{\alpha}_2} F(x)dx\right]$$

$$= -k_s^{US} + \boldsymbol{\rho}_H \int_{tk_r-A_H}^{tk_r+k_s^{US}-A_H} F(x)dx$$

$$\frac{\partial ECE^{TS}}{\partial \boldsymbol{\rho}_H} = \boldsymbol{\alpha}_2 - tk_r - \boldsymbol{\rho}_L \int_{G+k_s^{TS}}^{\boldsymbol{\alpha}_2} F(x)dx - (1-\boldsymbol{\rho}_L)\int_{G}^{\boldsymbol{\alpha}_2} F(x)dx$$

$$\frac{\partial ECE^{TS}}{\partial \boldsymbol{\rho}_L} = -k_s^{TS} - \boldsymbol{\rho}_H\left[\int_{G+k_s^{TS}}^{\boldsymbol{\alpha}_2} F(x)dx - \int_{G}^{\boldsymbol{\alpha}_2} F(x)dx\right] = -k_s^{TS} + \boldsymbol{\rho}_H \int_{G}^{G+k_s^{TS}} F(x)dx$$

Due to the parameter value range $tk_r > \boldsymbol{\alpha}_2$, easy to get $\partial ECE^{US}/\partial \boldsymbol{\rho}_H < 0$, $\partial ECE^{TS}/\partial \boldsymbol{\rho}_H < 0$, $\partial ECE^{US}/\partial \boldsymbol{\rho}_L < 0$ $\partial ECE^{TS}/\partial \boldsymbol{\rho}_L < 0$, proof.

Proof of property 8(2).

TS strategy and US strategy.

The same scale of investment in energy storage power stations k_s,

$$\frac{\partial ECE^{TS}}{\partial \boldsymbol{\rho}_H} - \frac{\partial ECE^{US}}{\partial \boldsymbol{\rho}_H} = \boldsymbol{\rho}_L \int_{tk_r+k_s-A_H}^{G} F(x)dx + (1-\boldsymbol{\rho}_L)\int_{tk_r-A_H}^{G} F(x)dx > 0$$

TS strategy and TN strategy.

Under the same electricity prices p_H during peak period,

$$\frac{\partial ECE^{TS}}{\partial \boldsymbol{\rho}_H} - \frac{\partial ECE^{TN}}{\partial \boldsymbol{\rho}_H} = \boldsymbol{\rho}_L \int_{G}^{G+k_s^{TS}} F(x)dx > 0$$

TS strategy and UN strategy

$$\frac{\partial ECE^{TS}}{\partial \boldsymbol{\rho}_H} - \frac{\partial ECE^{UN}}{\partial \boldsymbol{\rho}_H} = \boldsymbol{\rho}_L \int_{tk_r-A_H}^{G+k_s^{TS}} F(x)dx + (1-\boldsymbol{\rho}_L)\int_{tk_r-A_H}^{G} F(x)dx > 0$$

Under the TS strategy, the carbon emission level decreases faster with the increase in daytime probability than in the other three strategies.

Appendix 8
Proof property 9.

(1) Flat pricing

Find the first derivative of k_s^{US*} with respect to p_f for both sides of Equation (7), get $\rho_H \rho_L f(tk_r + k_s^{US*} - A_H)\frac{\partial k_s^{US*}}{\partial p_f} = \frac{\beta_s}{p_f^2}$, easy to get $\partial k_s^{US*}/\partial p_f > 0$.

(2) Time-of-use pricing

Find the partial derivative of p_f, γ, θ for Equation A6 and A8, respectively. As follows:

$$\frac{\partial^2 \pi^{TS}\left(k_s^{TS}, p_H^{TS}\right)}{\partial k_s^{TS} \partial p_f} = \rho_L\left[1 - \rho_H F\left(G + k_s^{TS}\right)\right] > 0,$$

$$\frac{\partial^2 \pi^{TS}\left(k_s^{TS}, p_H^{TS}\right)}{\partial k_s^{TS} \partial \gamma} = -(1-\theta) p_H^{TS} p_f \rho_H \rho_L f\left(G + k_s^{TS}\right) < 0$$

$$\frac{\partial^2 \pi^{TS}\left(k_s^{TS}, p_H^{TS}\right)}{\partial k_s^{TS} \partial \theta} = \gamma p_H^{TS} p_f \rho_H \rho_L f\left(G + k_s^{TS}\right) > 0$$

$$\begin{aligned}\frac{\partial^2 \pi^{TS}\left(k_s^{TS}, p_H^{TS}\right)}{\partial p_H^{TS} \partial p_f} &= \gamma(1-\theta)\left[1 - \rho_H \rho_L F\left(G + k_s^{TS}\right) - \rho_H (1-\rho_L) F(G)\right] \\ &\geq \gamma(1-\theta)\left[1 - \rho_L F\left(G + k_s^{TS}\right) - (1-\rho_L) F(G)\right] > \gamma(1-\theta)[1 - F(G)] > 0\end{aligned}$$

$$\begin{aligned}\frac{\partial^2 \pi^{TS}\left(k_s^{TS}, p_H^{TS}\right)}{\partial p_H^{TS} \partial \gamma} = &-(1-\theta)\left[2(1-\theta)p_H^{TS} - p_f\right] - p_f p_H^{TS} \rho_H \gamma (1-\theta)^2 \left[\rho_L f\left(G + k_s^{TS}\right)\right. \\ &\left. + (1-\rho_L) f(G)\right]\end{aligned}$$

When $p_f \leq 2(1-\theta)p_H^{TS}$ and $p_f \geq p_H^{TS}$, we can get $\theta \leq 0.5$, when $0 \leq \theta \leq 0.5$ and $p_H^{TS} \leq p_f \leq 2p_H^{TS}$, $\frac{\partial^2 \pi^{TS}(k_s^{TS}, p_H^{TS})}{\partial p_H^{TS} \partial \gamma} < 0$.

$$\begin{aligned}\frac{\partial^2 \pi^{TS}\left(k_s^{TS}, p_H^{TS}\right)}{\partial p_H^{TS} \partial \theta} = &\, 4(1-\theta)\gamma p_H^{TS} + A_L - \gamma p_f + p_f p_H^{TS} \rho_H \gamma^2 (1-\theta)\left[\rho_L f\left(G + k_s^{TS}\right)\right. \\ &\left. + (1-\rho_L) f(G)\right]\end{aligned}$$

When $A_L \geq \gamma p_f$, $\partial^2 \pi^{TS}(k_s^{TS}, p_H^{TS})/\partial p_H \partial \theta > 0$.

To sum up, we can get $\partial k_s^{TS*}/\partial p_f > 0$, $\partial k_s^{TS*}/\partial p_f > 0$, $\partial k_s^{TS*}/\partial \gamma < 0$, $\partial k_s^{TS*}/\partial \theta > 0$, $\partial p_H^{TS*}/\partial p_f > 0$. When $0 \leq \theta \leq 0.5$ and $p_H^{TS} \leq p_f \leq 2p_H^{TS}$, $\partial p_H^{TS*}/\partial \gamma < 0$. When $A_L \geq \gamma p_f$, $\partial p_H^{TS*}/\partial \theta > 0$, proof.

Appendix 9
Find the first derivative of ECE^{TS} with respect to θ, γ for Equation (10). Get

$$\begin{aligned}\frac{\partial ECE^{TS}}{\partial \theta} &= \gamma p_H^{TS}\left[1 - \rho_H \rho_L F\left(G + k_s^{TS}\right) - \rho_H(1-\rho_L) F(G)\right] \\ &= \gamma p_H^{TS}\left\{\rho_L\left[1 - \rho_H F\left(G + k_s^{TS}\right)\right] + (1-\rho_L)[1 - \rho_H F(G)]\right\}\end{aligned}$$

$$\frac{\partial ECE^{TS}}{\partial \boldsymbol{\gamma}} = (1-\boldsymbol{\theta})p_H^{TS}\left[\boldsymbol{\rho}_H\boldsymbol{\rho}_L F\left(G+k_s^{TS}\right)+\boldsymbol{\rho}_H(1-\boldsymbol{\rho}_L)F(G)-1\right]$$
$$= (1-\boldsymbol{\theta})p_H^{TS}\left\{\boldsymbol{\rho}_L\left[\boldsymbol{\rho}_H F\left(G+k_s^{TS}\right)-1\right]+(1-\boldsymbol{\rho}_L)[\boldsymbol{\rho}_H F(G)-1]\right\}$$

The range of values obtained by the parameters is easy to get $\partial ECE^{TS}/\partial\boldsymbol{\theta} > 0$, $\partial ECE^{TS}/\partial\boldsymbol{\theta} > 0$, $\partial ECE^{TS}/\partial\boldsymbol{\gamma} < 0$.

At the same peak price level p_H

$$\frac{\partial ECE^{TS}}{\partial\boldsymbol{\theta}} - \frac{\partial ECE^{TN}}{\partial\boldsymbol{\theta}} = \boldsymbol{\gamma} p_H\boldsymbol{\rho}_H\left[F(G)-\boldsymbol{\rho}_H\boldsymbol{\rho}_L F\left(G+k_s^{TS}\right)-\boldsymbol{\rho}_H(1-\boldsymbol{\rho}_L)F(G)\right]$$
$$= \boldsymbol{\gamma} p_H\boldsymbol{\rho}_H\boldsymbol{\rho}_L\left[F(G)-F\left(G+k_s^{TS}\right)\right]$$

$$\frac{\partial ECE^{TS}}{\partial\boldsymbol{\gamma}} - \frac{\partial ECE^{TN}}{\partial\boldsymbol{\gamma}} = (1-\boldsymbol{\theta})\boldsymbol{\rho}_H\left[\boldsymbol{\rho}_L F\left(G+k_s^{TS}\right)+(1-\boldsymbol{\rho}_L)F(G)-F(G)\right]$$
$$= (1-\boldsymbol{\theta})\boldsymbol{\rho}_H\boldsymbol{\rho}_L\left[F\left(G+k_s^{TS}\right)-F(G)\right]$$

Easy to get $\frac{\partial ECE^{TS}}{\partial\boldsymbol{\theta}} - \frac{\partial ECE^{TN}}{\partial\boldsymbol{\theta}} < 0$, $\frac{\partial ECE^{TS}}{\partial\boldsymbol{\gamma}} - \frac{\partial ECE^{TN}}{\partial\boldsymbol{\gamma}} > 0$.

Appendix 10

(1) Proof of Proposition 5

Expanded formula (11) can be obtained as formula A10

$$\max \boldsymbol{\pi}^{TSP}\left(k_s^{TSP}\right) = -(1-\boldsymbol{\theta})^2\boldsymbol{\gamma}(p_H)^2 + (A_H+\boldsymbol{\theta} A_L)p_H - \left(p_f+c\right)\left[A_H-\boldsymbol{\gamma}(1-\boldsymbol{\theta})p_H + \boldsymbol{\rho}_H(\boldsymbol{\alpha}_2-tk_r)-\boldsymbol{\rho}_L k_s^{TSP}\right] + \left(p_f+c\right)\boldsymbol{\rho}_H\left[\boldsymbol{\rho}_L\int_{G_1+k_s^{TSP}}^{\boldsymbol{\alpha}_2}F(x)dx + (1-\boldsymbol{\rho}_L)\int_{G_1}^{\boldsymbol{\alpha}_2}F(x)dx\right] - \boldsymbol{\beta}_r k_r - (\boldsymbol{\beta}_s - v\boldsymbol{\rho}_L)k_s^{TSP} \tag{A10}$$

Among which, $G_1 = tk_r + \boldsymbol{\gamma}(1-\boldsymbol{\theta})p_H - A_H$.

Find the first derivative and second derivative of the profit function in equation A11 on the capacity of the energy storage power station k_s^{TSP}, and obtain equation A11, respectively

$$\frac{\partial\boldsymbol{\pi}^{TSP}\left(k_s^{TSP}\right)}{\partial k_s^{TSP}} = \left(p_f+c\right)\boldsymbol{\rho}_L - \boldsymbol{\beta}_s + v\boldsymbol{\rho}_L - \left(p_f+c\right)\boldsymbol{\rho}_H\boldsymbol{\rho}_L F\left(G_1+k_s^{TSP}\right) \tag{A11}$$

$$\frac{\partial^2\boldsymbol{\pi}^{TSP}\left(k_s^{TSP}\right)}{\partial\left(k_s^{TSP}\right)^2} = -\left(p_f+c\right)\boldsymbol{\rho}_H\boldsymbol{\rho}_L f\left(G_1+k_s^{TSP}\right) < 0$$

Easy to get $\partial^2\boldsymbol{\pi}^{TSP}(k_s^{TSP})/\partial(k_s^{TSP})^2 < 0$. So the profit function is a concave function of the capacity of the energy storage station. There is an optimal capacity of energy storage power station, which maximises the profit of wind power generators. According to the FOC, when $\boldsymbol{\beta}_s \le (p_f+c+v)\boldsymbol{\rho}_L$, get equation (12).

(2) Proof of property 11

After the transformation of equation (10) and equation (12), formula A12 can be obtained

$$\rho_H \rho_L F\left(tk_r + \gamma(1-\theta)p_H - A_H + k_s^{TS*}\right) = \rho_L - \frac{\beta_s}{p_f}$$
$$\rho_H \rho_L F\left(tk_r + \gamma(1-\theta)p_H - A_H + k_s^{TSP*}\right) = \rho_L - \frac{\beta_s}{p_f + c} + \frac{v\rho_L}{p_f + c} \tag{A12}$$

At the same peak price level p_H, subtract the right side of the two formulas in Equation A12

$$\rho_L - \frac{\beta_s}{p_f + c} + \frac{v\rho_L}{p_f + c} - \left(\rho_L - \frac{\beta_s}{p_f}\right) = \frac{\beta_s}{p_f} - \frac{\beta_s}{p_f + c} + \frac{v\rho_L}{p_f + c} > 0$$

Since the distribution function $F(x)$ is a monotonic increment function, therefore $tk_r + \gamma(1-\theta)p_H - A_H + k_s^{TSP*} > tk_r + \gamma(1-\theta)p_H - A_H + k_s^{TS*}$, get $k_s^{TSP*} > k_s^{TS*}$.

Find the first derivative with respect to v and c for both sides of Equation (12), get

$$\rho_H \rho_L f\left(tk_r + \gamma(1-\theta)p_H - A_H + k_s^{TSP*}\right) \frac{\partial k_s^{TSP*}}{\partial c} = \frac{\beta_s - v\rho_L}{(p_f + c)^2} > 0$$

$$\rho_H \rho_L f\left(tk_r + \gamma(1-\theta)p_H - A_H + k_s^{TSP*}\right) \frac{\partial k_s^{TSP*}}{\partial v} = \frac{\rho_L}{p_f + c} > 0, \text{proof.}$$

(3) Property 12 proof

Under the TSP strategy, equation (13) is expanded to get equation A13

$$ECE^{TSP} = \rho_H(\alpha_2 - tk_r) + A_H - \gamma(1-\theta)p_H - \rho_L k_s^{TSP} - \rho_H\left[\rho_L \int_{G+k_s^{TSP}}^{\alpha_2} F(x)dx + (1-\rho_L)\int_G^{\alpha_2} F(x)dx\right] \tag{A13}$$

Contrast A13 with equation (10), it can be found ECE^{TSP} and ECE^{TS} only the size of energy storage power stations varies, formally consistent. Therefore, the ECE^{TSP} monotonic relationship with the parameters $\rho_H, \rho_L, \theta, \gamma$ is the same as that of ECE^{TS}.

At the same peak price level p_H

$$ECE^{TSP} - ECE^{TS} = -\rho_L\left(k_s^{TSP} - k_s^{TS}\right) + \rho_H \rho_L \int_{G+k_s^{TS}}^{G+k_s^{TSP}} F(x)dx$$
$$= \rho_L\left[\rho_H \int_{G+k_s^{TS}}^{G+k_s^{TSP}} F(x)dx - \left(k_s^{TSP} - k_s^{TS}\right)\right]$$

The range of values taken by the parameters obtained $ECE^{TSP} < ECE^{TS}$.

Source – author's own work (for all appendix).

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