Electricity Price-Driven Renewable Energy Station Value Evaluation Model: An Analysis of Economic Impact and Decision-Making Strategies

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Abstract. This paper proposes a new energy station value evaluation and optimization model driven by electricity price, which aims to more accurately reflect the impact of electricity price fluctuations on the economic value of new energy projects. By comprehensively considering meteorological factors, economic development, power consumption, power rationing and operating costs, a random variable model based on time series analysis and machine learning method is constructed, and Monte Carlo simulation technology is used for cash flow prediction and pricing analysis. The empirical research results show that this model can effectively improve the accuracy and stability of new energy project valuation, reduce the cognitive gap between investors and developers in market transactions, and promote the scientific and transparency of investment decisions. This study provides a powerful tool support for financial investment decision-making in the field of new energy and proposes that the combination of market trading mechanism and dynamic optimization model can be further studied in the future to better adapt to the complex and volatile market environment.

Keywords: Electricity Price Volatility, Renewable Energy Projects, Station Value Evaluation, SARMA, Monte Carlo Simulation, Machine Learning, Stochastic Variable Model, Risk Management, Investment Decision-making, Market Trading Mechanism

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1 Introduction

1.1 Research Background

As electricity market prices become increasingly market-driven, their volatility has risen. In the renewable energy sector, electricity prices are heavily influenced by supply and demand dynamics, policy changes, climate conditions, and the inherent intermittency of renewable power generation. Traditional valuation models often fail to capture these factors, yet electricity price volatility has become a key consideration in the valuation of renewable energy projects. By integrating electricity prices into the valuation model, financial investors in renewable energy projects can achieve more accurate cash flow projections, enabling them to make well-informed investment decisions.

This price-based model enables financial investors in renewable energy projects to better understand market risks and opportunities. By incorporating electricity price volatility, it improves investment decision-making and enhances the efficiency and transparency of the renewable energy market, leading to more informed, forward-looking investments.

1.2 Literature Review

With the liberalization of electricity markets, price fluctuations have become increasingly significant for new energy investments. Zhang et al. (2014)[1] highlighted that traditional Net Present Value (NPV) methods may underestimate project value, whereas the real options approach better captures market volatility. Zhao (2020)[2] further explored Discounted Cash Flow (DCF), real options, and Monte Carlo simulation, analyzing investment uncertainties driven by policy and market fluctuations.

Research also shows that increasing renewable energy penetration exacerbates electricity price volatility, impacting asset valuation. Böttger and Härtel (2022)[3] noted that renewables amplify price fluctuations, while Kohlscheen and Moessner (2022)[4] argued that green energy complicates valuation. Owolabi et al. (2023)[5] found that renewable penetration affects station cash flow and long-term income, and Zhao et al. (2023)[6] used game theory to compare pricing mechanisms' effects on electricity prices and new energy valuation.

Overall, electricity price fluctuations challenge investment decisions, making traditional NPV methods insufficient. Incorporating real options, Monte Carlo simulation, and game theory can better address market uncertainties and optimize investment strategies. However, most studies treat electricity prices as deterministic, overlooking their stochastic nature. In reality, prices follow diffusion processes (e.g., geometric Brownian motion)[7], which better capture volatility. Without this, research may underestimate risks and misrepresent long-term trends, leading to suboptimal valuations. Future studies should integrate stochastic process analysis and Monte Carlo simulations, widely used in finance but underutilized in renewable energy, to enhance valuation accuracy and decision-making under uncertainty.

1.3 Research Method

In this study, we abstract the new energy station as an option[8], The payoff of this option is the total future cash flows minus the initial investment made when purchasing the renewable energy plant.

$$P = \mathbb{E}\left[\int_0^T e^{-kt}(q_t * p_t - c_t)\,dt\right], \quad q_t \sim P_q(t), \quad p_t \sim P_p(t), \quad c_t \sim P_c(t) \qquad (1)$$

P: premium of the option (the value of renewable energy station).
q_t: Power generation at time *t*.
p_t: Average electricity price at time *t*.
c_t: Operating costs at time *t*.
$P_q(t)$, $P_p(t)$, $P_c(t)$: The stochastic processes that q_t, p_t and c_t obey.
k: is the market discount rate (or the bond's Yield to Maturity, YTM).
T: Remaining time of the project.

For financial investors with a defined return rate (k), finding the value of the power plant P requires determining the stochastic process of generation output ($P_q(t)$), electricity price ($P_p(t)$), and operating costs ($P_c(t)$) over the remaining life cycle of the project. Among these, operating costs are relatively fixed, the generation output follows a smoother stochastic process, while the electricity price is the most complex stochastic process.

In this study, we assume that the electricity price is affected by a variety of random variables, including the fluctuation of supply-demand relationship caused by relatively stable changes in power generation and load, the cost of thermal power generation in line with the diffusion process model, and the construction trend and policy factors of different types of new energy stations. Through the interaction of these independent variables, it can be combined into a random process to describe the change of electricity price, and the slice distribution of the random variable at the end of the period can be used to calculate the valuation of new energy stations.

2 Methodology

2.1 The Core Assumptions and Model Construction

The electricity selling price of new energy stations is composed of spot transaction price and long-term transaction price.

2.1.1 The Formation Mechanism of Electricity Spot Prices.

As shown in Figure 1, The spot price of electricity is mainly influenced by electricity consumption and renewable energy generation, both of which exhibit intraday cyclical and seasonal fluctuations. Electricity demand changes with the laws of production and life, and new energy generation is driven by natural conditions such as light and wind speed, so electricity prices also exhibit similar characteristics. When the output of new energy is high and the demand is low, the electricity price tends to decrease; On the

contrary, it may rise or even fluctuate violently. In addition, market bidding, transmission constraints, and standby unit scheduling result in fluctuating electricity prices on a periodic basis.

The impact of thermal coal prices on spot electricity prices is limited, as electricity prices are mainly determined by supply and demand, and thermal power enterprises often lock in coal prices through medium and long-term contracts, making short-term fluctuations difficult to directly transmit to the spot market. Only when there is an abnormal and significant fluctuation in the price of thermal coal, which significantly increases the marginal cost of thermal power, can it have a certain impact on the spot price of electricity.

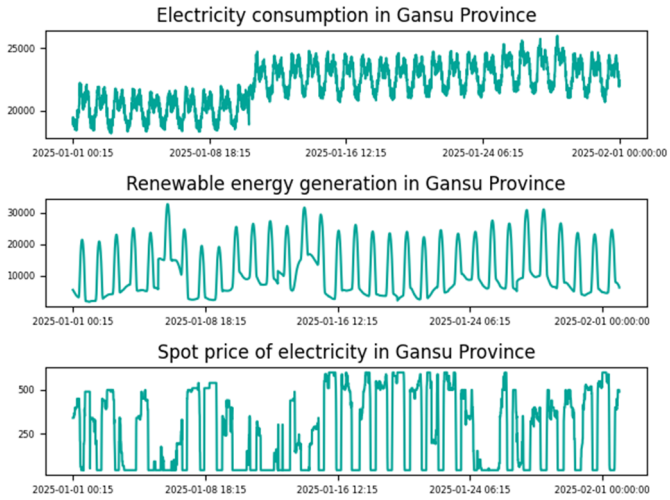

Fig. 1. Spot price of electricity in Gansu Province

2.1.2 The Formation Mechanism of the Long-Term Contract Prices.

When signing long-term trading contracts in new energy power plants, buyers and sellers usually use the comprehensive spot market price of the year of signing as the benchmark price for the long-term contract and combine it with predictions of future supply and demand trends to ultimately determine the contract electricity price.

Due to the all-weather power generation capability of wind power, its long-term contract pricing is usually based on the 24-hour spot price level throughout the year to reflect the market value of wind power's all-weather output. In contrast, photovoltaic power generation is mainly concentrated during the daytime, especially during lunchtime when the maximum electricity output is generated. Therefore, the long-term contract price of photovoltaic power plants is mainly based on the spot price level during lunchtime (such as 10:00-16:00) throughout the year to more accurately match the market value of photovoltaic electricity.

The impact of changes in thermal power costs on the long-term contract prices of new energy is extremely limited, and its effect is mainly reflected through the indirect impact of thermal power costs on spot prices.

2.1.3 Time Series Modeling.

Both new energy output and electricity consumption have intraday periodicity (such as photovoltaic day and night cycle) and seasonal fluctuation (difference between winter and summer), so it can be modeled by SARMA process modified by data distribution[9].

We also need to add two important long-term trend factors. Driven by policy support and technological progress, the overall output of new energy continues to rise. At the same time, with the acceleration of economic development and electrification process, the power consumption of the whole province also shows a long-term growth trend. These two factors jointly affect the supply and demand pattern of the power market. To express the long-term trend of the growth of the number of new energy stations and the growth of power consumption in the province, we can use the function of decreasing first-order derivative for modeling to ensure that the growth rate gradually slows down over time, to conform to the actual situation. In this paper, logarithmic growth models are selected.

Therefore, to describe the dynamic changes in the spot price of electricity, we can start with the following key variables to establish the mathematical models of wind energy, photovoltaic, power demand, futures price and new energy supply in turn:

1. Wind power generation modeling: The Sarma process is used to describe the short-term fluctuation of wind speed, and the logarithmic growth term is added to represent the long-term growth trend of wind energy resources:

$$R_w(t) = g(SARMA(p_w, q_w, P_w, Q_w, T_w, t), D_w) + \alpha_w * ln(1 + \beta_w * t) \quad (2)$$

2. Photovoltaic power generation modeling: The Sarma process is used to characterize the intraday and seasonal fluctuations of light, and the growth of long-term photovoltaic resources is captured by the logarithmic growth term:

$$R_s(t) = g(SARMA(p_s, q_s, P_s, Q_s, T_s, t), D_s) + \alpha_s * ln(1 + \beta_s * t) \quad (3)$$

3. Load modeling: the Sarma process is used to describe the short-term periodicity of power demand, and the logarithmic growth model is used to describe the rise in power consumption caused by long-term economic growth:

$$L(t) = g(SARMA(p_l, q_l, P_l, Q_l, T_l, t), D_l) + \alpha_l * ln(1 + \beta_l * t) \quad (4)$$

4. The short-term variability of curtailment can be modeled as a function of historical renewable energy generation and power demand using Support Vector Regression (SVR):

$$W_{curt}(t) = SVR\big(R_w(t), R_s(t), L(t)\big) \quad (5)$$

5. Thermal power cost price modeling: Geometric Brownian motion (GBM) is used to represent the long-term trend and jump diffusion model (JD) is used to deal with sudden fluctuations in the market:

$$C(t) = GBM(\mu, \sigma, c_0) + JD(\lambda_c, J_c) \tag{6}$$

6. Spot price modeling: Spot price is jointly determined by wind resources, photovoltaic resources, power demand and futures prices, and is affected by market noise. The price function f can be fitted by historical data. In China, the influencing factors of spot prices are published by the provincial power trading center, and the influence mode is more direct. Therefore, even a simple regression algorithm can get a good market equilibrium price function:

$$dY_s(t) + \theta Y_s(t)dt = f\big(R_w(t), R_s(t), L(t), C(t), w_{curt}(t)\big)\, dt + \epsilon_t \tag{7}$$

7. The long-term contract price is affected by the spot price at the time of signing the contract and the future supply and demand relationship:

$$w_{daylight}(t) = \begin{cases} 1, & if\ t_{sunrise} \le Daytime(t) \le t_{sunset} \\ 0, & otherwise \end{cases} \tag{8}$$

$$Y_w\big(t_{sig}, t_{end}\big) = \frac{1}{w_s + w_{dsd}} * \left(w_s \frac{\int_0^{t_{sig}} w_t Y_s(t)\, dt}{\int_0^{t_{sig}} w_t\, dt} + w_{dsd} \frac{\int_{t_{sig}}^{t_{end}} Y_s(t)\, dt}{t_{end} - t_{sig}}\right) \tag{9}$$

$$Y_s\big(t_{sig}, t_{end}\big) = \frac{1}{w_s + w_{dsd}} * \left(w_s \frac{\int_0^{t_{sig}} w_t w_{daylight}(t) Y_s(t)\, dt}{\int_0^{t_{sig}} w_t\, dt} + w_{dsd} \frac{\int_{t_{sig}}^{t_{end}} w_{daylight}(t) Y_s(t)\, dt}{t_{end} - t_{sig}}\right) \tag{10}$$

The stochastic process equation for electricity price is derived above. By performing Monte Carlo simulations on these stochastic processes, the option price in Formula 1 can be determined. Table 1 provides definitions and descriptions of the variables used in the formulas.

Table 1. Notation, Description, and Estimation Approach

Symbol	Description	Determination Method
$R_w(t)$:	Wind power generation time series	Historical data regression
$R_s(t)$:	Photovoltaic power generation time series	Historical data regression
$L(t)$:	Electricity demands time series	Historical data regression
$C(t)$:	Thermal power cost price	Historical data regression
$Y_s(t)$:	Spot price modeling	Historical data regression
p, q:	Orders of autoregression (AR) and moving average (MA)	Historical data regression

P, Q:	Orders of seasonal autoregression (SAR) and seasonal moving average (SMA)	Historical data regression
T:	Seasonal period (e.g., 24 hours, 12 months)	Historical data regression
g:	Distribution correction function	NaN
D:	Distribution adjustment parameter (e.g., log-normal transformation)	Historical data regression
α, β:	Logarithmic growth model parameters	Trading Center disclosure
μ:	Drift rate of the Geometric Brownian Motion (long-term trend)	Historical data regression
σ:	Volatility of futures prices	Historical data regression
λ_c:	Jump intensity parameter (frequency of price jumps)	Historical data regression
J_c:	Magnitude of price jumps	Historical data regression
f:	Market Equilibrium Price Function (MEPF)	Historical data regression
ε_t:	Market noise term, representing unmodeled random influences	Historical data regression
$w_{daylight}(t)$:	Daylight weight function	Policy rules
$W_{curt}(t)$:	Short-term curtailment weight function	Historical data regression
w_t:	Weight function	Historical data regression
w_{dsd}:	Weight adjustment for the future period	User specified
t_{sig}:	Time of contract signing	User specified
t_{end}:	Contract end time	User specified

2.2 Empirical Analysis and Case Study

2.2.1 Station Selection.

The selection criteria for stations in this case study are based on the following considerations: wind power and photovoltaic stations with a stable operational history to ensure data reliability; a diversified range of station scales to facilitate the analysis of scale effects on valuation; and comprehensive data availability, including historical power generation, electricity prices, and operation and maintenance costs, with coverage over a complete seasonal cycle to enhance the accuracy of model calibration.

To maintain benchmark consistency, the total investment value of each station is adopted as the standard metric for project quotations, expressed in Yuan per watt. This approach ensures comparability across different projects, thereby improving the precision of pricing calibration and comparative analysis.

Table 2 summarizes the basic information of photovoltaic and wind farm stations selected according to the above criteria, including station type, transaction time and

purchase and sale quotation (unit: yuan/watt). P1 and P2 represent centralized and distributed photovoltaic power stations respectively, while W1, W2 and W3 are wind farm stations. The trading time reflects the market-oriented trading time of the station and indicates the time node when it enters the market. Bid and ask respectively to represent the full investment valuation of the station by investors or developers in the market using traditional valuation methods, from which we can observe the valuation levels and differences of different types of stations in the market.

Table 2. Case study station information (The life cycle of all stations after transaction is 20 years.)

Station	Type	Location	Trading Time	Ask (Yuan/watt)	Bid (Yuan/watt)
P1	Photovoltaic	Shanxi	2020.3	3.15	2.58
P2	Photovoltaic	Xinjiang	2020.9	3.30	3.76
W1	Wind power	Gansu	2019.8	8.35	7.30
W2	Wind power	Xinjiang	2020.5	6.29	5.57
W3	Wind power	Shanxi	2020.8	7.13	8.67

2.2.2 Backtesting and Analysis.

Table 3 shows the valuation results of new energy stations calculated based on the new valuation algorithm proposed in this paper. Compared with the traditional method, this algorithm uses machine learning models to estimate the future fluctuation distribution of electricity price and then calculates the market value of the station.

Table 3. The estimation results are based on the new algorithm proposed in this paper

Station	Estimation Data Period	MEPF Regression Method	Value (Yuan/watt)
P1	2018.1—2020.3	SVR	2.62
P2	2018.5—2020.9	SVR	2.93
W1	2018.1—2019.8	GBDT	7.75
W2	2018.6—2020.5	GBDT	6.90
W3	2019.1—2020.8	MLP	7.46

To validate the accuracy of the valuation model for new energy power stations, this study proposes a long-term cash flow prediction method based on time series regression. Since the valuation model employs the SARMA model for time series fitting, the cash flow regression uses a different time series algorithm—specifically, a Transformer-based encoder structure[10] adept at capturing periodic fluctuations—to ensure a fair comparison and avoid bias caused by using the same modeling approach. Using actual cash flow data from the trading day, the model extrapolates to predict the total cash flow for the next 20 years. According to the China International Capital Corporation (2023)[11], the government-guided discount rate for onshore wind projects in China ranges from 6% to 8%; thus, a discount rate of 7% is adopted in this study.

As shown in figure 2, Monte Carlo simulation has generated multiple potential cash flow paths, by calculating the discount value of each path, the discounted cash flow distribution as shown in Figure 3 can be obtained.

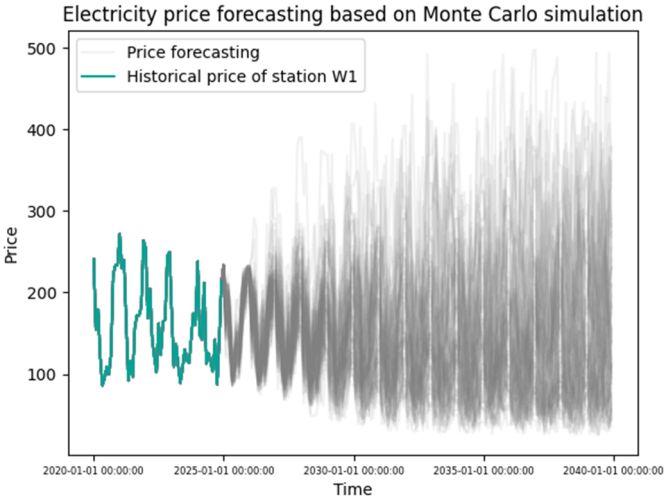

Fig. 2. Calculation of future electricity price trend by Monte Carlo method

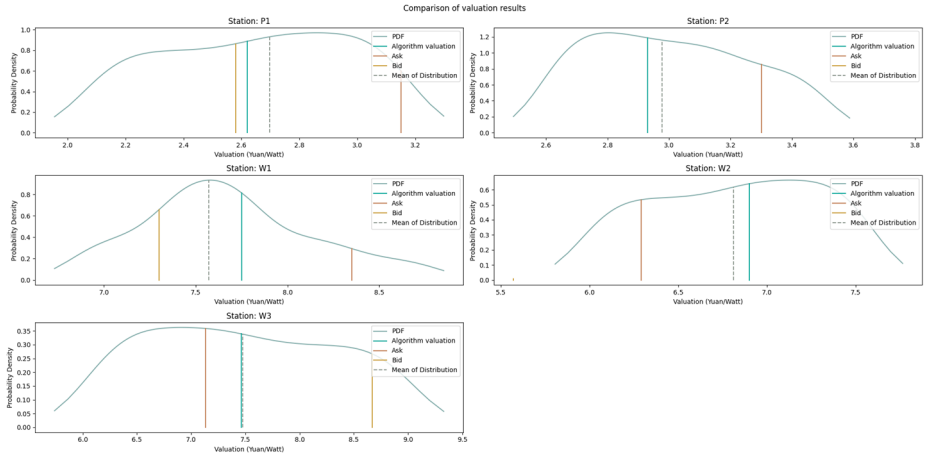

Fig. 3. Comparison of valuation results

Overall, the algorithm valuation of each new energy station is very close to the average of the valuation probability distribution, indicating that the valuation algorithm used has high stability and can effectively capture the market expectation of the station value. The valuation results are highly consistent with the value distribution characteristics reflected by Monte Carlo simulation. This stability and accuracy provide reliable references for market participants, helps to narrow the valuation differences between buyers and sellers, and promotes the transaction to reach consensus.

3 Conclusion and Outlook

The new energy station value evaluation model based on electricity price driven proposed in this paper can effectively solve the problem of insufficient understanding of market uncertainty, especially electricity price volatility in traditional methods. This study combines the time series model and machine learning method and uses Monte Carlo simulation to comprehensively consider the impact of meteorological conditions, economic development, electricity consumption, power rationing factors and operating costs on the value of new energy stations.

The empirical research results show that this model can more accurately capture the market expectations for the future cash flow of the station, provide a stable and reliable valuation reference, significantly reduce the cognitive differences between investors and promote the smooth conclusion of market transactions. In addition, this model is not only suitable for wind energy and photovoltaic power generation projects, but also has certain universality and expansibility, and can provide scientific decision support for financial investors in the field of new energy.

Future research can further deepen the dynamic optimization ability of the model and explore the impact of more complex market trading mechanism on the valuation of new energy stations, providing a more practical and guiding decision-making tool for the field of new energy investment.

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