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Risk-return analysis of clean energy grid project investment based on integrated ISM and Monte Carlo model

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Abstract

To solve the problem of complex and difficult to quantify factors affecting investment returns and risks in clean energy power grids, this study comprehensively applies the interpretive structural model and Monte Carlo model to the analysis of investment risk-returns in clean energy power grid projects. The interpretive structural model is utilized to analyze project investment returns, while the Monte Carlo model is used to analyze project investment risks. The project investment risk is based on the factor analysis of project investment returns, and key risk factors are identified through 1000 simulations, and the impact of these risks on project returns is quantified. By combining the two, the investability of the project is analyzed. The results showed that grid electricity prices, kilowatt hour subsidies, technology learning rates, total annual sunshine hours, and system power generation efficiency were key factors driving investment returns. The average expected value of investment return was about 20%, and the probability of investment return below 6% was close to 0. The overall project is worth investing in. From this, it can be seen that the research designed investment risk-return analysis methods for clean energy grid projects can effectively distinguish the main factors affecting investment returns and risks, and pre simulate the risk situation of returns. This study can provide reference for investor decision-making.

Keywords: Clean Energy, Investment Risk, Investment Return, ISM, Monte Carlo

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Introduction

As the increasing severity of global climate change and the increasing scarcity of fossil fuels, clean energy has gradually gained attention due to its advantages of pollution-free and widespread resource distribution. The power grid project (PGP) is the core of the clean energy utilization system, and the focus of the PGP is on stability. However, the supply of clean energy will also change with changes in the external environment, leading to fluctuations in the level of energy supply, which in turn affects the stability of the power grid, and has an impact on investment returns and risk [1-3]. The research mainly uses two models, Interpretive Structural Modeling (ISM) and Monte Carlo model, to analyze the investment risk and return of clean energy grid projects. The ISM model can identify the relationships between various elements in a system, thereby helping decision-makers understand the structure of complex systems and the dynamic relationships between elements [4-6]. The Monte Carlo model can evaluate the

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performance of the system under uncertain conditions and quantify the risk of the system through a large number of random simulations. By combining the two, it is possible to systematically and comprehensively evaluate the investment risks and benefits of clean energy grid projects under uncertain conditions [7-9]. Therefore, this study combines the ISM model with the Monte Carlo model to provide scientific basis for investment in clean energy grid projects and strong support for decision-making. The research can be divided into four main parts. The first part introduces the theme of investment risk and return analysis for clean energy grid projects. The second part proposes evaluation methods for investment risk and return of clean energy grid projects, namely ISM model return analysis and Monte Carlo model risk analysis. The third part conducts simulation analysis to test and analyze the factors affecting investment risk and return. The fourth part draws research conclusions.

1. Literature Review

In recent years, the investment problem of power grid has attracted widespread attention. Gruber et al. analyzed the expected profit of winter investment based on the cost of power system winterization, combined with electricity demand estimation and power plant shutdown prediction. The results showed that the profit expectation of winter investment in the power system was positive, but due to the high investment risk and the uncertainty of power generation failure in low-temperature environments, the cost of winter investment was relatively high, which is higher than the cost of social power shortage [10]. DeMenno et al. analyzed the resilience and sustainability of the US power grid system, using financial sector stress testing methods to test the power sector and analyze its investment situation. The results showed that multi sector coordinated investment projects were often more resilient [11]. Bera et al. analyzed the economic benefits of energy storage system projects in the market and proposed a comprehensive investment evaluation and solidification framework. This framework evaluated the income situation throughout the project lifecycle after considering the impact of income estimation after degradation costs on investment returns. The results showed that the method was effective and could provide decision-makers with decision-making basis [12].

In the application of the ISM model, the Kumar R team applied the ISM model to bibliometric and visual analysis, and applied VOSviewer and Biblioshiny software for literature analysis. The results showed that after 2000, the number of annual publications using ISM technology showed a rapid growth trend. In addition, through visual analysis, the most influential authors, sources, articles, countries, and organizations could be identified, providing reference for future research [13]. Zayed EO et al. used the ISM model to analyze the obstacles to sustainable supply chain management in Egyptian industry. The study collected data through expert interviews and analyzed the relationships between elements using the ISM model, providing recommendations for the sustainable development of Egyptian industry based on this [14].

In the application of Monte Carlo modeling, Christensen A P et al. applied Monte Carlo simulation to psychological measurement and analyzed the number of correctly identified factors in multivariate data. The study analyzed the efficacy of different community psychological detection algorithms under different community data conditions through Monte Carlo simulation. The outcomes denoted that Fast-greedy, Louvain, and Walktrap algorithms had relatively better accuracy [15]. Soleimani H et al. used Monte Carlo simulation to analyze the groundwater resources drinking suitability in rural areas of Iran, with a focus on assessing the non-carcinogenic health risks of nitrates. By evaluating the potential health risks of four exposure groups, the results showed that the region had a high concentration of nitrate, which may have an impact on the physical health of local residents [16].

This study combines the Monte Carlo model with the ISM model and applies it to the investment evaluation of power grid energy projects. Compared with other studies, it has more quantitative characteristics and evaluates returns and risks separately, which is more targeted.

2. Methodology

When conducting risk-return analysis on investment in clean energy grid projects, two models, ISM model and Monte Carlo model, are studied and established. The ISM model is used for investment return analysis of clean energy grid projects, while the Monte Carlo model is used for investment risk analysis of clean energy grid projects, which is based on investment return analysis.

2.1 Investment risk-return analysis of clean energy grid projects using ISM model

The ISM model is an effective method that can classify the hierarchical elements and levels of many influencing factors on investment returns of clean PGPs [17]. In a complex chain of influencing factors, the ISM model can explore the surface, intermediate, and fundamental factors that affect the investment efficiency of photovoltaic power generation. The correlation model of influencing factors established in the study is shown in Figure 1.

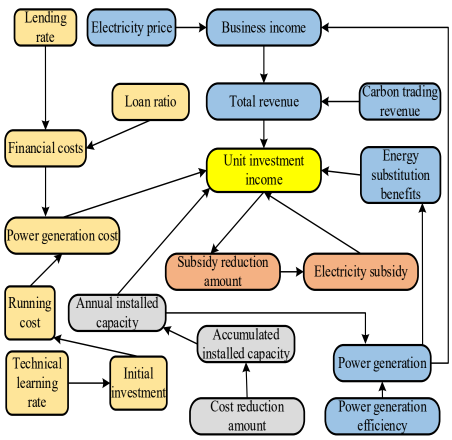

Figure 1. Factor correlation model

By establishing a correlation chart of the factors influencing the investment returns of photovoltaic power generation, 26 main influencing factors can be extracted. Specifically, it includes financial costs, loan interest rates, loan ratios, operation and maintenance costs, power generation costs, CO_2 emissions reduction, grid electricity prices, annual power generation, initial investment, etc. These factors have direct or indirect impact relationships, forming a complex hierarchical chain of factors. The specific influencing factors are indicated in Table 1.

Table 1. Table of impact factors

Number of influencing factors	Name of influencing factors	Number of influencing factors	Name of influencing factors
S1	business income	S14	Reduction in electricity subsidy
S2	lending rate	S15	Energy substitution benefits
S3	Financial costs	S16	System power generation efficiency
S4	Loan ratio	S17	Unit environmental cost
S5	CO_2 reduction	S18	Annual power generation
S6	Electricity subsidy	S19	Initial investment
S7	Technical learning rate	S20	Annual newly added installed capacity
S8	Operation and maintenance costs	S2I	Carbon emission trading revenue
S9	Cost reduction amount	S22	Accumulated installed capacity
S10	Operation and maintenance rate	S23	Carbon emission coefficient for electricity production
S11	Power generation cost	S24	Carbon emission trading price
S12	On grid electricity price	S25	Total revenue
S13	Annual total sunshine hours	S26	Unit investment income

An ISM model variable system is constructed based on the influencing factor table, which takes unit investment return as the core variable and constant variables such as technology learning rate, total annual sunshine hours, unit environmental cost, carbon emission coefficient of electricity production, and operation and maintenance rate. The other variables are auxiliary variables, and the specific variable system is shown in Table 2.

Table 2. Variable system table

Variable name	Company	Variable symbols
Unit investment income	/	D
Accumulated installed capacity	kW	R
Electricity subsidy	yuan/kWh	Ps
Initial investment	Ten thousand yuan	Cint
Annual newly added installed capacity	kW	Ra
Reduction in electricity subsidy	yuan/kWh	Pr
Cost reduction amount	Ten thousand yuan	Cr
CO_2 reduction	t	c
Power generation cost	Ten thousand yuan	Ct
Running cost	Ten thousand yuan	Co
Financial costs	Ten thousand yuan	Cf
Total revenue	Ten thousand yuan	Pt
Business income	Ten thousand yuan	Pb
Carbon emission trading revenue	Ten thousand yuan	Pd
Energy substitution benefits	Ten thousand yuan	B
interest rate	/	O
Power generation	10000 kWh	G
System power generation efficiency	/	T1
On grid electricity price	yuan/kWh	Pp
Carbon emission trading price	yuan/t	Pd
Technical learning rate	/	Lr
Annual total sunshine hours	h	H
Unit environmental cost	yuan/kWh	Eu
Carbon emission coefficient for electricity production	t/kWh	a
Operation and maintenance rate	/	p

According to the system dynamics model, the unit investment return is a key model variable that depends on costs, subsidies, and returns, and can be used to calculate the level of power generation return in the power grid, as shown in formula (1).

$$D = {(P_t + B \times P_s \times G - G_t)}/{C_{int}} \quad (1)$$

In formula (1), P_t represents income, P_s represents electricity subsidy, B represents energy substitution efficiency, G represents annual power generation, G_t represents power generation cost, and C_{int} represents initial investment. The initial investment is as shown in formula (2).

$$C_{int}(t)=C_{int}(t-1)-C_r \quad (2)$$

In formula (2), C_r represents the amount of cost reduction. The amount of cost reduction is shown in formula (3).

$$C_r(t) = C_{im} \times L_R \times \frac{\ln\frac{R(t)}{R(t-1)}}{\ln 2} \quad (3)$$

In formula (3), L_R represents the technical learning rate. R(t) represents the cumulative installed capacity, calculated using formula (4).

$$R(t) = R(t-1) + R_\alpha \quad (4)$$

In formula (4), R_α represents the newly added installed capacity. The financial cost is reflected in the annual loan interest, which is determined by the loan ratio and interest rate level. The calculation method is as shown in formula (5).

$$C_f = C_{int} \times \theta \times \delta \quad (5)$$

In formula (5), θ represents the loan ratio and δ represents the interest rate level. The cost of power generation is based on financial costs, initial investment, and operation and maintenance costs. The calculation method is as shown in formula (6).

$$C_t = C_f + C_{int} + \beta + C_{int} \quad (6)$$

In formula (6), β represents the proportion of operation and maintenance costs. Due to the influence of external environment, the power generation of new energy generation often varies in different regions and systems, and the power generation efficiency also varies in different time periods. The annual power generation is shown in formula

(7).

$$G = R \times H \times \varphi \quad (7)$$

In formula (7), H represents annual sunshine time, R represents cumulative installed capacity, and φ represents power generation efficiency. The system's operating revenue is based on the annual power generation, as shown in formula (8).

$$P_b = P_p \times G \quad (8)$$

In formula (8), P_p represents the grid electricity price. Clean energy grids do not generate greenhouse gas emissions during the profitable process, and are a low-carbon technology that can generate a portion of carbon emissions trading revenue through carbon emissions trading. Because of the lack of a carbon emission trading mechanism in China, the trading price of the EU's carbon emission system is used, as shown in formula (9).

$$P_c = C \times P_d \quad (9)$$

In formula (9), C represents carbon emissions, and P_d represents carbon emission trading prices. Then the total income is as shown in formula (10).

$$P_t = P_b + P_c \quad (10)$$

Due to the clean energy grid replacing fossil energy generation, it has significant environmental benefits, as shown in formula (11).

$$B = E_G \times G \quad (11)$$

In formula (11), E_G represents the unit environmental cost. In addition, in order to encourage the development of clean energy, China has a certain subsidy policy for clean energy power generation, as shown in formula (12).

$$P_s(t) = P_s(t-1) - P_r \quad (12)$$

In formula (12), P_r represents the reduction in electricity subsidies. According to the logical relationship between two factors, the correlation between different factors is shown in Table 3.

Table 3. Table of influencing factors

Factor number	Number of influencing factors	Factor number	Number of influencing factors
S1	S11, S9, S8, S10	Sl4	S11
S2	S1	Sl5	S26
S3	S1	Sl6	S15
S4	S11	Sl7	S12
S5	S26	S18	S22, S23
S6	S10, S8	S19	S23
S7	S4, S11	S20	S12
S8	S5	S2I	S20
S9	S12, S7	S22	S26
S10	S8	S23	S5
S11	S9	S24	S26
S12	S9, S8, S1, S6	S25	S26
S13	S12	S26	S9

According to Table 3, the adjacency matrix A for all factors can be derived, and the matrix elements are defined as formula (13).

$$A = \begin{cases} a_{ij} = 1, S_i \text{ Directly affecting } S_j (i, j = 1,2 \cdots 26) \\ a_{ij} = 1, S_i \text{ does not Directly affecting } S_j (i, j = 1,2 \cdots 26) \end{cases} \quad (13)$$

According to the adjacency matrix, an reachable matrix is established, as shown in formula (13).

$$(A + I) \neq (A + I)^2 \neq \cdots \neq (A + I)^r \neq (A + I)^{r+1} = (A + I)^n \quad (14)$$

In formula (14), I represents an identity matrix of the same order as the adjacency matrix, with diagonal elements of 1 and non-diagonal elements of 0, representing the maximum number of transfers. The reachable matrix can divide various elements in the system into three hierarchical sets: the antecedent set, the reachable set, and the highest level element set. The antecedent set represents the set of elements corresponding to all rows with element 1 in a certain element column. The reachable set represents the set of elements corresponding to all columns with 1 element in a certain element row. The set of superlative elements represents a set of elements whose reachable set and antecedent set are the same, which can be expressed as formula (15).

$$R'(Si) \cap A(Si) = R(Si) \quad (15)$$

In formula (15), $R(Si)$ represents the reachable set, $A(Si)$ represents the antecedent set, and $R'(Si)$ represents the set of highest level features. By using formula (15), the nodes at this level can be obtained, which in turn determines the hierarchy of factors affecting the investment returns of the power grid.

2.2 Monte Carlo model investment risk-return analysis of clean energy grid projects

The clean energy grid investment risk-return model constructed based on the ISM model is deterministic, meaning that the variables in the model are fixed and unchanged. However, in real production and operation situations, there are often certain risks, and all influencing factors may not be deterministic, but are influenced by various uncertain factors, which can lead to investment risks. Therefore, in order to analyze the investment risks of clean energy grid projects, a Monte Carlo model was used to evaluate the system under uncertain conditions. In the Monte Carlo model, the net present value model is used as the core mathematical model, as shown in formula (16).

$$NPV = \sum_{t=0}^{T} \frac{C_t}{(1+r)^t} \quad (16)$$

In formula (16), NPV represents net present value, C_t represents net cash flow, t represents year, T represents project period, and r represents discount rate. The Monte Carlo model is a simulation method that uses random sampling. Its basic principle is to treat the input variable as a random variable and calculate the probability distribution of the system output through extensive simulation. Monte Carlo simulation can help analyze the impact of different variables on system output, identify key risk factors, and quantify the impact of these risks on project returns. Due to the fact that the investment risks of clean energy grid projects mainly come from five main aspects: market risk, technical risk, policy risk, financial risk, and operational risk, based on the experience of investment return analysis, it is determined that the risks mainly come from five uncertain factors: grid electricity price, kilowatt hour subsidies, technical learning rate, total annual sunshine hours, and system power generation efficiency. On this basis, define the model input variables as indicated in Table 4.

Table 4. Model input variable table

Uncertain factors	Probability distribution form	Probability distribution description
On grid electricity price	Triangular distribution	Minimum value of 75%, most likely value of 85%, maximum value of 100%
Electricity subsidy	Triangular distribution	Minimum value 31%, most likely value 38%, maximum value 44%
Technical learning rate	uniform distribution	Min 19%, Max 24%
Annual total sunshine hours	Normal distribution	Expected 1260, standard deviation 85
System power generation efficiency	uniform distribution	Min 70%, Max 85%

After determining the input variables and their probability distribution, random sampling can be performed to extract sample values from the pre-defined probability distribution of the input variables. In this step, a single value needs to be selected from the distribution interval of each element to generate a random sample, which is repeatedly repeated and operated based on mathematical logic and core mathematical models. To fully evaluate the uncertainty of the project, the Monte Carlo model will conduct a large number of repeated simulations. This study conducted 10000 simulations, each time generating a different set of random samples and calculating the corresponding output results. Afterwards, all simulation results are collected for statistical analysis.

3. Results

In the results analysis section, investment returns and risks were analyzed separately. In both sections, important influencing factors and simulation results were analyzed. Risk simulation analysis was based on the analysis of returns.

3.1 Simulation analysis results of investment returns

When conducting investment return simulation analysis, the first step was to analyze the various elements of investment returns, identify the main factors driving the growth of investment returns, and based on this, conduct simulation. The first level node set table is shown in Table 5.

Table 5. The first level node set table

Number	$R(S_i)$	$A(S_i)$	Intersection
S1	S1, S6, S26	S1, S2, S12	S1
S2	S3, S2, S6, S26	S2	S2
S3	S3, S12, S6, S26	S3	S3
S4	S4, S12, S6, S26	S4, S5, S7, S8, S9, S10, S11	S4
S5	S4, S5, S12, S6, S26	S5	S5
S6	S6, S26	S6, S23	S6
S7	S4, S12, S7, S6, S26	S7, S8, S9, S10, S11	S7
S8	S4, S12, S7, S8, S6, S26	S8, S9, S10, S11	S8
S9	S4, S12, S7, S8, S9, S6, S15, S17, S19, S22, S23, S26	S9	S9
S10	S4, S12, S7, S8, S10, S6, S26	S10	S10
S11	S4, S12, S7, S8, S11, S6, S26	S11	S11
S12	S12, S17, S19, S22, S23, S26	S9, S12, S13, S14	S12
S13	S15, S13, S17, S19, S22, S23, S26	S13	S13
S14	S15, S14, S17, S19, S22, S23, S26	S14	S14
S15	S15, S26	S9, S12, S13, S14, S15, S16, S18, S23	S15
S16	S15, S16, S26	S16	S16
S17	S17, S22, S26	S9, S12, S13, S14, S17, S18, S19	S17
S18	S15, S17, S18, S22, S23, S26	S18	S18
S19	S17, S19, S22, S26	S9, S12, S13, S14, S19	S19
S20	S20, S22, S26	S20, S21	S20
S21	S20, S21, S22, S26	S21	S21
S22	S22, S26	S9, S12, S13, S14, S17, S22	S22
S23	S15, S23, S26	S9, S12, S13, S14, S18, S23	S23
S24	S24, S26	S24, S25	S24
S25	S24, S25, S26	S25	S25
S26	S26	S1, S26	S26

From Table 5, numbers 1 to 26 indicate different combinations of reachable and antecedent sets, which represent direct relationships between different elements. For example, the intersection of S1, S6, S26 and S1, S2, and S12 was S1, indicating that S1 is directly influenced by S6, S26, S2, and S12. From the element relationship, S26 was the first level node. Removing this part of the elements will result in the second level node. By continuously removing elements, the 6th node is finally obtained, as shown in Table 6.

Table 6. The 6th level node set table

Number	$R(S_i)$	$A(S_i)$	Intersection
S12	S12	S12	S12
S6	S6	S6	S6
S7	S7	S7	S7
S13	S13	S13	S13
S16	S16	S16	S16

From Table 6, S1, S6, S7, S13, and S16 were the factors that occupy the core position and had the highest independence in the project, respectively. These factors include grid electricity prices, kilowatt hour subsidies, technology learning rates, total annual sunshine hours, and system power generation efficiency. These factors had an impact on the overall project without being disturbed by other factors, namely critical nodes. When considering investment priorities, it is necessary to focus on monitoring and optimizing these independently influential factors, which are the key factors driving the growth of investment returns. The initial investment and power generation simulation are shown in Figure 2.

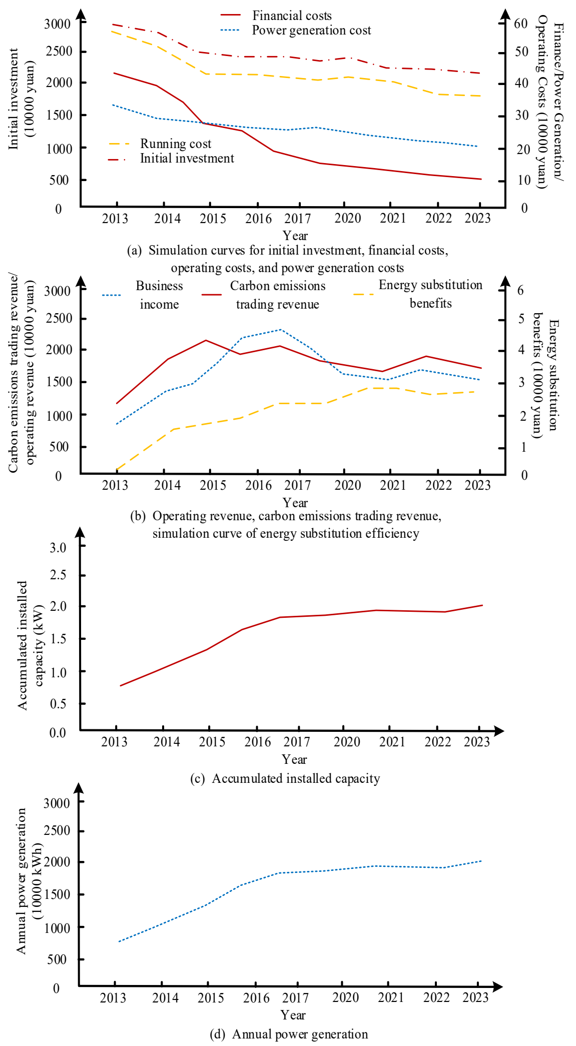

Figure 2. Initial investment and power generation simulation results

From Figure (a), the initial investment, financial costs, operating costs, and power generation costs all showed a downward trend, with overall changes relatively stable. The initial investment decreased from around 30 million yuan to around 24 million yuan. From Figure (b), both carbon emissions trading revenue and operating revenue showed a trend of first increasing and then decreasing, with the main turning point located between 2016 and 2017, while the energy substitution effect showed a fluctuating upward trend. From Figure (c), the cumulative installed capacity showed an overall upward trend, with a relatively gentle upward trend since 2016, rising from around 0.7kw to around 2.2kw. From Figure (d), the annual power generation also showed an overall upward trend, rising from around 7.5 million kW to around 22 million kW. The simulation of unit investment return is shown in Figure 3.

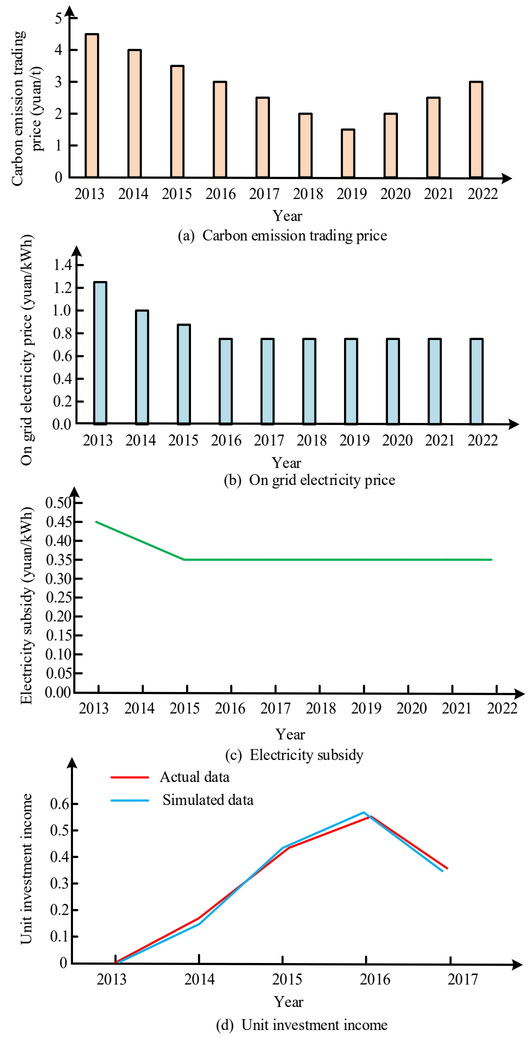

Figure 3. Simulation results of unit investment returns

From Figure (a), the carbon emissions trading price showed a trend of first decreasing and then increasing, with the main turning point located in 2019. From Figure (b), the grid electricity price showed a slow downward trend, and has been showing a flat trend since 2016. From Figure (c), the electricity subsidy showed a trend of first decreasing and then stabilizing, with the main turning point located between 2014 and 2015. From Figure (d), the simulated data of the system was more in line with the actual data, with both lines reaching a peak of around 0.6, showing a trend of first increasing and then decreasing after reaching the peak in 2016.

3.2 Results of investment risk simulation analysis

When conducting investment risk simulation analysis, the probability and sensitivity of investment return were analyzed from two perspectives. Sensitivity analysis was mainly used to analyze the impact of key factors on investment risk, as shown in Figure 4.

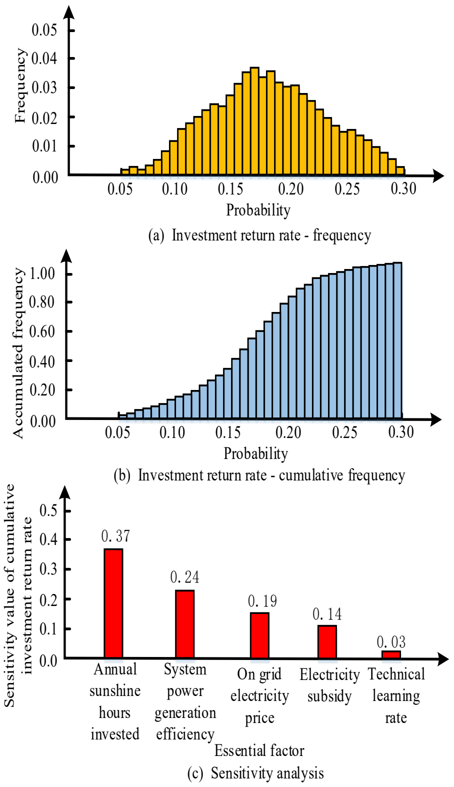

Figure 4. Investment risk simulation results

Through extensive simulations, the average expected value of investment return was about 20%, with a peak of around 37% and a valley of around 5%. However, the overall probability of a valley occurring was relatively low. The probability of an investment return between 13% and 25% was close to 50%, while the probability of an investment return below 6% was close to 0. From this, the overall investment risk of the project was low and the returns were good. In addition, from the perspective of influencing factors, the impact of annual sunshine hours on investment returns reached 0.37, with the greatest impact. Next was the system power generation efficiency, with an impact value of 0.24. The impact of grid electricity prices on investment returns was 0.19. The impact of electricity subsidies on investment returns was 0.14. The impact of technology learning rate on investment returns was minimal, only 0.03. In the process of paying attention to project investment returns, the first thing to focus on was the annual sunshine hours, followed by the system power generation efficiency, while the influence of technology learning rate was not sufficient to a certain extent.

Conclusions

The investment return and risk assessment of clean energy grid projects are key issues that investors should pay attention to before investing. Research used the ISM model to the hierarchical analysis of investment returns in clean energy grid projects, and used the Monte Carlo model to the simulation evaluation of investment risks in clean energy grid projects. The findings indicated that in the investment return analysis of clean energy grid projects, the simulated data line of the system showed a trend of first increasing and then decreasing with the actual data line, reaching a peak of around 0.6 in 2016, and the two lines were relatively close. In addition, the model deduced that the key factors driving investment returns were grid electricity prices, kilowatt hour subsidies, technology learning rates, total annual sunshine hours, and system power generation efficiency. From the simulation results of the Monte Carlo model, the investment return rate was between 5% and 37%, with an average expected value of 20%. The probability of a return rate between 13% and 25% was close to 50%, while the probability of an investment return rate below 6% was close to 0. This project has certain investment value. From this, the risk return analysis method for PGP investment designed in the research can effectively screen important factors and accurately estimate the project's returns and risks. Although the research designed methods are relatively effective, they only focus on clean energy grids. Considering the scalability of mixed use projects between clean energy grids and ordinary grids, conducting expansion analysis on such projects is the future research direction.

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