Research on Financial Performance Evaluation of Listed Companies in the Electric Power Industry: Based on Factor Analysis and Cluster Analysis

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Abstract: Against the backdrop of the "dual carbon" goals and energy structure transformation, the power industry, as a pillar industry of the national economy, must adopt a scientific financial performance evaluation system. This paper takes 78 listed power companies as its research subjects, constructing an evaluation system comprising 11 financial indicators based on the principles of appropriateness, scientific rigor, and systematicity. Utilizing SPSS 26 software, factor analysis and cluster analysis were employed to conduct empirical and comprehensive evaluations, with the cluster results used to analyze issues. The study found that there is significant variation in financial performance among enterprises, with different categories of enterprises exhibiting varying strengths and weaknesses in profitability, debt-repayment capacity, and other areas. Some enterprises are facing development bottlenecks. The article proposes recommendations tailored to different types of enterprises and the overall industry situation to help power enterprises enhance performance, achieve sustainable development under the "dual carbon" goals, and strengthen competitiveness.

Keywords: Electric Power; Industry; Factor Analysis; Cluster Analysis; Financial Performance

1. Introduction

1.1 Research Background and Purpose

Driven by global energy structure adjustments and the "dual carbon" goals, the power industry, as a pillar of the national economy, is facing transformation and challenges. The rapid iteration of new energy technologies and the development of smart grids are accelerating the reshaping of the industry's competitive landscape. Power sector-listed companies must balance social responsibility with financial sustainability. Financial performance can directly reflect the efficiency of resource allocation, risk resilience, and value creation capabilities during a company's strategic transformation. To this end, this paper takes listed power companies classified under the China Securities Regulatory Commission's industry classification in 2012 as its research object. Using SPSS 26 software, factor analysis is employed to extract common factors, determine weights, and uncover the intrinsic logic of financial conditions. Cluster analysis is then used to classify companies and identify differences, thereby constructing a financial performance evaluation system. Finally, improvement suggestions are proposed for different companies, providing references for the healthy development of listed power companies and supporting the industry in achieving high-quality development under the new development paradigm.

1.2 Research Significance

At the theoretical level, this paper introduces factor analysis and cluster analysis into the financial performance evaluation of listed companies in the power industry, revolutionizing traditional research paradigms. Factor analysis reduces dimensions to extract the underlying structure of financial indicators, constructing a scientific evaluation framework; cluster analysis then precisely classifies companies based on this framework, breaking through the limitations of a "one-size-fits-all" approach. The combination of the two methods addresses the shortcomings of traditional evaluations, providing a new methodological framework for industry financial research and driving the advancement of research toward greater precision and scientific rigor.

At the practical level, this study holds significant value for multiple stakeholders: for businesses, it enables the identification of strengths and weaknesses through key factors, optimizes resource allocation, facilitates strategic decision-making, and leverages clustering results for benchmarking management; for investors, an objective evaluation framework assists in quickly identifying companies with different performance profiles, thereby reducing investment risks; for regulatory authorities, classification outcomes support the formulation of differentiated policies and guide the healthy development of the industry; the research also explores pathways for business synergy, driving the power industry to achieve green and low-carbon transformation while ensuring energy supply, thereby unifying economic and social benefits.

2. Research Design

2.1 Sample Selection and Data Source

This paper selects 83 A-share listed companies in the electric power industry as the initial sample according to the classification standards of the Guidelines for Industry Classification of the Securities and Futures Commission (2012 Revision). In determining the final sample companies, this paper strictly follows the following criteria: firstly, exclude the listed companies labeled as ST; secondly, exclude the companies with incomplete financial data; finally, exclude the companies with abnormal fluctuation of financial data to ensure the stability and comparability of financial data. Based on the above screening conditions, this paper finally selects the 2023 financial data of 78 listed companies in the electric power industry as the research sample. To ensure the authenticity and availability of the research results, all the data in this paper come from the database of CSMAR.

2.2 Indicator System Construction

Following the principles of appropriateness, scientificity, and systematicity, this paper selects 11 suitable financial indicators from the indicators reflecting the profitability, solvency, operation, and development ability of enterprises to construct a comprehensive evaluation system of financial performance. In this paper, the larger the value of the indicators means the better the business condition, and the indicators with less risk are defined as "positive indicators", and vice versa as "negative indicators" [1]. (See Table 1).

Table 1. Financial Indicator System

Financial capacity	Financial Indicators	Nature of indicators	Indicator variable
Profitability	Return on invested capital	Positive	X_1
	Return on assets	Positive	X_2
	Net profit margin on total assets	Reverse	X_3
	Return on net assets.	Positive	X_4
Solvency	Current Ratio	Positive	X_5
	Quick Ratio	Positive	X_6
	Gearing ratio	Reverse	X_7
Operating Capacity	Total Asset Turnover Ratio	Positive	X_8
	Accounts Receivable Turnover Ratio	Positive	X_9
Development capacity	Fixed Assets Growth Rate	Positive	X_{10}
	Owner's equity growth rate	Positive	X_{11}

2.3 Research Methodology

2.3.1 Factor analysis method

Factor analysis is a multivariate statistical method, which mainly involves transforming a large amount of variable data with certain correlations into fewer common factors through matrix calculation and statistical analysis according to the principle of eigenvalue greater than one. After extracting the common factors, the rotation operation is used to make each common factor as independent of each other as possible and to maximize the explanation of the variation of the original data. Finally, the extracted metrics are interpreted to establish their relevance to the actual concepts. This method makes the raw data more concise and easy to analyze and significantly improves the efficiency of data analysis. The factor analysis model is described as follows:

$X_1= \alpha_{11}F_1+ \alpha_{12}F_2+... +\alpha_{1m}F_m+ \varepsilon_1$

$X_2= \alpha_{21}F_1+ \alpha_{22}F_1+... +\alpha_{2m}F_m+ \varepsilon_2$

......

$X_p= \alpha_{p1}F_1+ \alpha_{p2}F_2+... +\alpha_{pm}F_m+ \varepsilon_p$

In the equation, X_1, X_2,..., $X_p$are observable random vectors, F_1, F_2,..., F_m are principal factors, α is the factor loading coefficient, and ε is the special factor [2].

2.3.2 Cluster analysis

Cluster analysis is a multivariate statistical analysis method based on the idea of "clustering by class", because the research samples have a certain degree of similarity in the observation indicators, according to the similarity of the observation indicators to find a statistic that can summarize these indicators, and according to these statistics to carry out cluster analysis [3].

This paper adopts the Q-type clustering method based on factor analysis and applies K-means cluster analysis to classify enterprise samples into four categories to give reasonable opinions and suggestions. The steps of K-means clustering method are mainly as follows: firstly, randomly selecting K initial clustering centers; secondly, for each data point, calculating the distance between it and the clustering centers, and grouping it into the cluster corresponding to the closest clustering center to the cluster corresponding to the closest cluster center; three, recalculate the cluster centers for each cluster; and four, repeat steps two and three until the cluster assignments are no longer changed or a preset maximum number of iterations is reached [4].

3. Empirical Analysis

3.1 Sample Data Preprocessing

Before the implementation of factor analysis, given the different nature of the financial data, it is necessary to carry out the preprocessing of the financial indicators. The pre-processing process mainly consists of two steps: first, for the reverse indicator processing, in the selected financial indicators, the gearing ratio belongs to the reverse indicator, using the method of taking the inverse of its positive; second, given the selected financial indicators there is a difference in the scale of the need for standardization. In this paper, the default Z-score standardization of the SPSS26 system is used to standardize the sample data [5].

3.2 Factor Analysis

3.2.1 Feasibility analysis

This paper utilizes SPSS26 to perform KMO and Bartlett tests on the preprocessed 11 financial indicators to determine the feasibility of the study. The test results are shown in Table 2, the KMO value reached 0.768, which is greater than 0.6, indicating that there is a correlation between the variables analyzed, i.e. the sample data can be factor analyzed. Meanwhile, the significance of Bartlett's test is 0.000, which is less than the queer value of 0.05, i.e., the original hypothesis is rejected, indicating that there is a significant correlation between the data, so the sample is suitable for factor analysis.

Table 2. KMO and Bartlett Test

KMO Number of sampling aptitude.		0.768
Bartlett's test of sphericity	Approximate card	966.976
	df	55
	Sig.	0.000

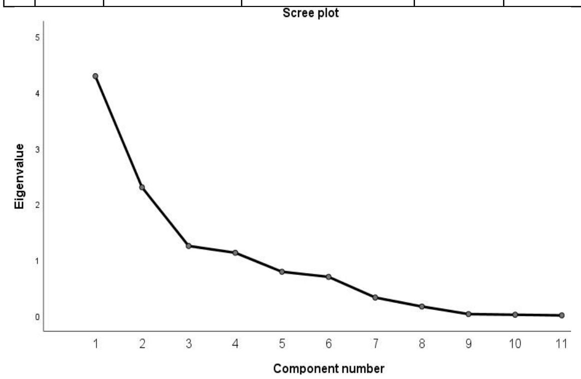
3.2.2 Factor extraction

In factor analysis, common factor variance refers to the variance explained by multiple variables in relation to a particular latent factor. Common factor variance is the variance explained by all variables collectively. The larger the variance, the greater the proportion of variance explained by these variables, indicating that the extracted common factor has a stronger explanatory power. In this paper, we use SPSS26 software to propose the common factors of the data after preprocessing using principal component analysis and use the variance maximization rotation method to obtain the eigenvalues, eigenvalue contribution rate, and cumulative contribution rate after the rotation of the correlation matrix (see Table 3). It can be seen that there are four factors whose initial eigenvalues are greater than 1 and the cumulative variance contribution rate after rotation reaches 81.528%, indicating that these four factors can explain the vast majority of the information of the original index data, and can be used for factor analysis on behalf of the original index data.

Table 3. Total Variance Explained

	Initial eigenvalue			Extracted loadings sum of squares			Rotated loadings sum of squares		
	Total	Variance %	Cumulative %	Total	Variance	Cumulative	Total	Variance	Cumulative
1	4.291	39.007	39.007	4.291	39.007	39.007	3.763	34.209	34.209
2	2.3	20.908	59.915	2.3	20.908	59.915	2.673	24.304	58.513

3	1.249	11.358	71.274	1.249	11.358	71.274	1.283	11.668	70.181
4	1.128	10.254	81.528	1.128	10.254	81.528	1.248	11.347	81.528
5	0.787	7.159	88.686						
6	0.697	6.332	95.018						
7	0.327	2.971	97.99						
8	0.166	1.508	99.498						
9	0.03	0.271	99.769						
10	0.018	0.166	99.935						
11	0.007	0.065	100						



Figuer 1. Scree plot

Extraction method: principal component analysis.

Meanwhile, to make the results of factor extraction more detailed, the judgment can be aided by the gravel plot. As can be seen in Figure 1, the eigenvalue curve tends to flatten in the fourth common factor backward, which further supports the reasonableness and scientificity of the factor extraction results.

3.2.3 Naming of public factors

To make the factors have naming interpretability, this paper adopts the Kaiser normalized great variance method to rotate the factor loading matrix orthogonally and name the public factors according to the rotated matrix, and the results are shown in Table 4, which shows that each of the four extracted public factors is irrelevant, which indicates that it has reasonableness, and therefore the four extracted public factors are named as F_1, F_2, F_3, F_4.

Table 4. Component Matrix after Rotation

Financial Indicators	Component			
	F_1	F_2	F_3	F_4
Return on invested capital	0.973	0.101	0.08	0.077
Return on assets	0.962	0.156	0.092	0.08
Net profit margin on total assets	0.942	0.25	0.099	0.064
Return on net assets	0.927	0.003	-0.027	0.078
Current ratio	0.133	0.956	-0.119	0.041
Quick ratio	0.134	0.951	-0.135	0.037
Gearing ratio	0.112	0.854	0.147	-0.102
Total Asset Turnover	0.108	0.075	0.783	0.133
Accounts receivable turnover	0.03	-0.146	0.754	-0.126
Fixed Assets Growth Rate	-0.057	-0.039	0.103	0.842
Owner's equity growth rate	0.285	0.014	-0.112	0.686

Extraction method: Principal Component Analysis.

Rotation method: Kaiser normalized maximum variance method.

a. The rotation has converged after 5 iterations.

The loading coefficients of the common factor F_1 in the return on invested capital, return on assets, net profit margin on total assets, and return on net assets are 0.973, 0.962, 0.942, 0.927 respectively, which mainly reflect the company's profitability, and thus named as profitability factor; the loading coefficients of the common factor F_2 in the current ratio, quick ratio, return on net assets are 0.956, 0.686, 0.927, 0.686 and 0.956 respectively. 0.956, 0.951, 0.854, of which the current ratio and quick ratio mainly reflect the company's short-term solvency, gearing ratio reflects the long-term solvency of the enterprise, so F_2 named solvency factor; public factor F_3 in the total asset turnover, accounts receivable turnover rate of the loading factor of 0.783, 0.754, respectively, much higher than other indicators, and these two indicators mainly reflect the company's profitability. These 2 indicators mainly reflect the operating ability of the enterprise, so they are named operating ability indicators; the loading coefficients of the common factor F_4 on the growth rate of fixed assets and the growth rate of owner's equity are 0.842 and 0.686, which are significantly higher than the other indicators, and these 2 indicators can reflect the growth of the company's assets, so they are named as the development ability factor.

3.2.4 Evaluation of public factor scores and comprehensive scores

Through the component score coefficient matrix obtained by SPSS26 (as shown in Table 5), the score expression of each sample company on the four public factors can be obtained, and then the scores of listed companies in the power industry on the four public factors can be calculated. Subsequently, based on the share of variance explained by each factor, the scores are weighted and summed to obtain a comprehensive factor variance F.

Table 5. Matrix of Factor Scores

Financial Indicators	Factor			
	F_1	F_2	F_3	F_4
Return on invested capital	0.274	-0.049	-0.003	-0.034
Return on assets	0.264	-0.024	0.01	-0.029
Net profit margin on total assets	0.249	0.016	0.024	-0.038
Return on net assets	0.277	-0.091	-0.091	-0.033
Current Ratio	-0.05	0.371	-0.045	0.042
Quick ratio	-0.047	0.368	-0.059	0.038
Gearing ratio	-0.051	0.344	0.16	-0.073
Total Asset Turnover	-0.049	0.072	0.627	0.116
Accounts Receivable Turnover	-0.021	-0.019	0.591	-0.098
Fixed Assets Growth Rate	-0.11	0.018	0.1	0.712
Owner's equity growth rate	0.022	-0.012	-0.099	0.543

Extraction method: Principal Component Analysis.

Rotation method: kaiser normalized maximum variance method.

Component score.

Common factor score expression:

$F_1=0.973X_1+0.962X_2+0.942X_3+0.927X_4+0.133X_5+0.134X_6+0.112X_7-0.108X_8+0.030X_9-0.057X_{10}+0.285X_{11}$

$F_2=0.101X_1+0.156X_2+0.250X_3-0.003X_4+0.956X_5+0.951X_6+0.854X_7-0.075X_8-0.146X_9-0.039X_{10}+0.014X_{11}$

$F_3=0.080X_1+0.092X_2+0.099X_3-0.027X_4-0.119X_5-0.135X_6+0.147X_7+0.783X_8+0.754X_9+0.103X_{10}-0.112X_{11}$

$F_4=0.077X_1+0.080X_2+0.064X_3+0.078X_4+0.041X_5+0.037X_6-0.102X_7+0.133X_8-0.126X_9+0.842X_{10}+0.686X_{11}$

To comprehensively analyze the comprehensive performance of enterprises, the scores of each factor are weighted by the proportion of the variance contribution rate of each factor to the cumulative contribution rate respectively, and the composite score is calculated, thus obtaining the formula for calculating the composite score of the electric power industry [4]:

$F=41.96\%*F_1+29.81\%F_2+14.31\%F_3+13.92\%F_4$

3.3 Cluster Analysis

In this paper, through the comprehensive factor score expression, based on the idea of dimensionality reduction from the high to the bottom of the ranking, to get the score ranking of the sample enterprises, and then use K-means cluster analysis method, the use of factor analysis extracted from the power industry listed companies profitability, solvency, operating capacity and development capacity of four public factors for cluster analysis, the results are shown in Table 6, the power industry listed companies into four categories [6].

Table 6. Classes to which Each Listed Company in the Electric Power Industry Belongs

Classification	Number	Company name
First category	6	Shimano Energy, New China Harbor, Hengsheng Energy, Fuling Power, Min Dong Power, Zhongmin Energy
Second category	25	Tongbao Energy, Hangzhou Thermal Power, Star Power, Fukuneng, Inner Mongolia Huadian, Bao New Energy, Longyuan Power, Ganneng, Huadian Energy, Jiangsu Guoxin, Fuchun Environmental Protection, Dixon, Yangtze River Power, GCL Energy, Guodian Power, Three Gorges Water Conservancy, South Network Energy Storage, Huaneng Hydropower, Yongtai Energy, Guangxi Energy, Leshan Electric Power, Qianyuan Electric Power, Guang'an Aizhong, Shenzhen Energy, Guiguan Electric Power

Third Category	34	Baitong Energy, Zhenergy Power, Shaanxi Energy, Chuaneng Power, Jiaze Xinergy, Guangzhou Development, ChuanTou Energy, Shenergy Stock, Ningbo Energy, Energy Saving Wind Power, Sui HengYun A, Wanergy Power, Guotou Electric Power, Huaneng International, China General Nuclear Power, Tianfu Energy, Huadian International, JinKai Xinergy, Gansu Energy, Zhejiang Xinergy, China Nuclear Power, Changyuan Electric Power, Lixin Energy, JinkoSolar Technology, Three Gorges Energy, Yinxing Energy, Shanghai Electric Power, Guangdong Electric Power A, Hubei Energy, Jingneng Power, Datang Power Generation, Jiantou Energy, Jidian Power, Huayin Power
Category 4	13	Lianmei Holdings, Jiangsu Xinneng, Solar Energy, Jinfang Energy, Shennan Electricity A, Meiyan Jixiang, Zhaoxin, Chendian International, Jin Control Power, Xichang Electricity, Shaoneng, Yu Energy Holdings, Langfang Development

Through the clustering analysis results, combined with the mean values of the four public factors and comprehensive performance for classification mean comparison, the different characteristics of the four types of enterprises are obtained, as shown in Table 7.

(1) The first category of companies is conservative and robust, including six listed companies such as Shimano Energy, New China Harbor, and Hengsheng Energy, with an average composite factor score of 1.142007, which is located in the first place of the sample companies, and the rankings of the composite scores of the single companies are also relatively advanced. The mean score of the solvency and profitability factor of these companies is higher than the composite factor and ranked first among the four types of companies; the mean score of the operating ability factor is lower than the composite factor and ranked second; and the mean score of development ability factor is much lower than the composite factor score, which is only -0.149161, which pulls down the composite ranking. These companies belong to the mature leading industry, with excellent performance in profitability and solvency, but weak development ability and weak growth. In future development, they should prioritize the strengthening of development ability and operational efficiency based on maintaining the advantages in profitability and solvency, and synchronize with the formulation of dynamic strategic objectives, the establishment of an independent innovation department, and the implementation of dual-track appraisal system, to safeguard the rational allocation of resources through system upgrades.

Table 7. Classification Mean Comparison

Category	Profitability	Solvency	Operating ability	Development ability	Composite Factor
I	1.374074	1.958078	0.017417	-0.149162	1.142007
II	0.239081	-0.264709	0.612941	-0.634856	0.020770
III	0.089439	-0.393857	-0.329466	0.749773	-0.022682
IV	-1.327876	0.635414	-0.325090	-0.671225	-0.507700

(2) The second category of companies is efficiency maintenance enterprises, including 25 listed companies such as Tongbao Energy, Hangzhou Thermal Power, Star Power, etc., with a composite factor score of 0.020770, which is located in the second place of the sample companies. This type of enterprise has a higher mean score of operating ability factor, which is located in the first place of the four types of companies; the mean score of profitability factor is larger than the score of comprehensive factor, which is ranked second; solvency and development ability factor are lower than the mean score of comprehensive factor, which is ranked third among the four types of enterprises. From the above analysis, this category of companies is characterized by operational capacity and profitability, but solvency and development capacity drag down the composite score, reflecting their over-reliance on operational efficiency. In their future development, these companies should prioritize strengthening their solvency and long-term growth potential while maintaining their operational and profitability advantages; at the same time, they should explore high-value-added businesses and rely on digital tools to further enhance their operational efficiency; and at the same time, they should establish a dynamic risk assessment mechanism to balance short-term turnaround efficiency and long-term growth investment.

(3) The third category of enterprises is potential growth enterprises, including 35 listed companies such as Baitong Energy, Zhenneng Power, Shaanxi Energy, etc., with a mean value of the comprehensive factor score of -0.022682, ranking third. This type of enterprise has the highest development ability factor score, which is in the first place of the four types of companies, much higher than the composite factor score; the profitability factor score is higher than the composite factor score although it is only in the third place; and the solvency and operating ability factor scores are lower than the composite factor score. From the above analysis, this type of enterprise has greater development potential, profitability is not as good as the first two types of enterprises, but it has a positive role in promoting the development of the enterprise, and other capabilities are weaker and more in line. Companies in the third category should prioritize the enhancement of profitability and financial soundness based on maintaining the advantage of development potential; synchronize the strengthening of operational efficiency to shorten the return cycle of inputs; and set up a risk hedging mechanism to balance high growth and sustainability.

(4) The fourth category of companies is the decline of distressed enterprises, including 13 listed companies such as Lianmei Holdings, Jiangsu Xinneng, solar energy, etc., with a composite factor score of -0.507700, which is at the bottom of the sample companies. This type of enterprise solvency factor score mean value is the highest, located in the fourth place, indicating that the enterprise has a better ability; the operating ability factor score mean value is negative, but higher than the average comprehensive factor score, indicating that the enterprise is stronger; profitability factor and development ability factor score mean value is in the fourth place, and the profitability is only -1.327876, pulling down the comprehensive factor score mean value. Based on maintaining solvency, enterprises in the fourth category should prioritize the divestment of inefficient assets and explore transformation paths; introduce external capital or participate in industry consolidation, and reshape competitiveness with the help of partner resources; and synchronize the implementation of the cost limit compression and strive for policy relief.

4. Conclusion and Recommendation

This paper through the factor analysis and cluster analysis two methods, selected the appropriate financial indicator system of China's power industry listed companies for comprehensive performance evaluation, and found that China's power industry listed companies' overall financial performance is poor, accounting for the frequency of the company with the highest number of medium-low level, up to 60.25%. Based on this, the following suggestions are put forward for the listed companies in China's electric power industry.

4.1 Classification and Optimization of Strategic Positioning

Listed companies in the power industry need to accurately analyze their resource endowment and competitive situation, and implement differentiated strategies based on the stage of development. Mature enterprises, should focus on breaking through growth bottlenecks, and realize transformation and upgrading by exploring new business models such as integrated energy services and virtual power plants; growing enterprises should focus on cost control and profitability enhancement while expanding installed capacity and capturing market share; distressed enterprises should decisively divest their inefficient assets, and focus their resources on business areas with transformation potential. In the process of strategic adjustment, closely track the "dual-carbon" target, the construction of new power systems, and other policy guidance, and adjust the business layout promptly.

4.2 Promote Innovation and Efficiency Improvement

At the level of technological innovation, listed companies need to increase R&D investment in key areas such as clean energy, smart grid, and energy storage technology, accelerate technological breakthroughs and transformation of results through the establishment of special funds and joint laboratories, and enhance core competitiveness in new energy equipment manufacturing, intelligent operation, and maintenance. At the same time, the company will deeply promote digital transformation, use big data and artificial intelligence to build an intelligent production management system, realize the whole life cycle management of power generation equipment and load optimization scheduling, reduce operating costs, and improve energy efficiency. In terms of innovation mechanism, it has set up an incubation fund to support potential projects, implemented a fault-tolerance mechanism to encourage technology attempts; introduced cross-field talents in digitalization, carbon management, and other fields, and set up a diversified team to break the traditional mindset and create an innovative atmosphere, to inject a new kinetic energy for the enterprise's development.

4.3 Optimize Financial Structure and Risk Management

For highly indebted enterprises, the capital structure can be optimized through debt-to-equity conversion and asset securitization to reduce the gearing ratio and improve the debt maturity, to alleviate the pressure of short-term debt repayment. Actively use green financial tools, issuing carbon-neutral bonds, green asset-backed securities, etc., to broaden low-cost financing channels and provide financial security for low-carbon transformation. In terms of risk management, we have established a perfect risk early warning and assessment system, utilized financial derivatives to hedge market risks such as energy prices, interest rates, and exchange rates, and strengthened the study of external risks such as policies and regulation and formulated response strategies in advance. At the same time, we have formulated liquidity contingency plans, reasonably reserved funds, and optimized cash flow management to ensure that the enterprise maintains stable operations under adverse circumstances such as industry fluctuations and emergencies.

4.4 Deepening Green Transformation and Policy Synergy

Listed companies should actively respond to the national low-carbon development strategy, accelerate the layout of wind power, photovoltaic, hydrogen energy, and other clean energy projects, gradually reduce the dependence on traditional thermal power, and increase the proportion of clean energy installed capacity. Take the initiative to participate in the carbon trading market, through carbon quota management, carbon asset management, and other means, the enterprise energy saving and emission reduction achievements into economic benefits; actively develop green certificate resources, expand the green certificate trading business, to realize the win-win situation of environmental benefits and economic benefits. Pay close attention to the national energy planning, renewable energy subsidies, and other policy dynamics, in-depth study of policy guidance and support priorities, actively declare projects that meet the policy requirements and strengthen communication and cooperation with local governments to create a good policy environment for the sustainable development of enterprises.

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