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Optimization of Enterprise Financial Performance Evaluation System Based on AHP and LSTM Against the Background of Carbon Neutrality

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ABSTRACT

This study focuses on meticulously examining energy companies' financial performance, incorporating the principles of environmentally sustainable development. The study employs a comprehensive assessment approach that integrates various metrics from different departments of these enterprises. These abstract indicators are primarily quantified using the analytic hierarchy process (AHP), emphasizing incorporating low-carbon indicators, such as research and development (R&D) in renewable energy, into the evaluation framework. Subsequently, the study utilizes the long short-term memory (LSTM) model to evaluate the performance of individual departments within these companies. Ultimately, the study provides an overarching evaluation of the financial performance of energy enterprises. The proposed model demonstrates its effectiveness in practical testing, achieving an evaluation error of just 1.7%. Moreover, the research also scrutinizes the implications of these financial evaluation results for the transition toward a low-carbon paradigm.

KEYWORDS

Energy Enterprises, Financial Performance Evaluation, Financial Prediction, Long Short-Term Memory, Low Carbon Development

INTRODUCTION

The pace of socio-economic development is accelerating while the global environmental climate is undergoing perpetual change. The environment continues to endure ceaseless pollution and degradation, giving rise to phenomena like atmospheric haze, which profoundly impact human existence. The imperative of a low-carbon economy is gaining recognition from an increasing number of nations and individuals, imposing fresh demands on enterprise development, reducing energy consumption, and mitigating pollution and carbon dioxide emissions (Akbari, 2022). Since energy enterprises involve high energy consumption and substantial pollutant emissions, such entities should actively embrace energy-saving measures and emission reduction initiatives. Over time, the world's total energy supply has steadily expanded, accompanied by ongoing adjustments to and optimizations

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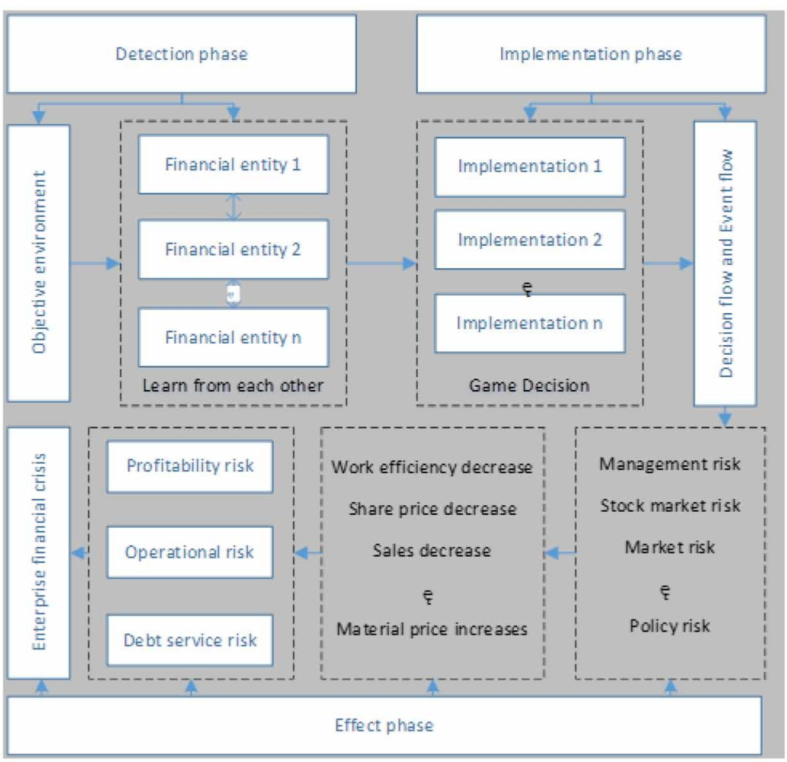
of the energy structure (Benjaafar et al., 2013). The exploration and study of new energy sources have garnered significant attention from numerous countries, who perceive it as a pivotal avenue for enhancing energy security, addressing climate deterioration, and achieving sustainable development objectives. Backed by supportive national policies, renewable energy technologies are maturing, their deployment is expanding in scale, and their economic viability is improving (Chen et al., 2019). The continuous evolution and transformation of the new energy industry are instigating substantial changes in the development of energy companies. In addition to vigorously pursuing further energy utilization, traditional energy enterprises must engage in long-term planning for their advancement, integrating resources from various existing departments and accurately evaluating their financial performance to facilitate precise strategic deployment (Cho et al., 2019).

Most traditional financial studies focus solely on examining the development of financial crises from the perspective of economic activities. However, they lack a systemic viewpoint that considers the evolutionary process of financial problems. As a result, they encounter challenges in identifying the underlying causes of corporate finance issues, rendering them ineffective for corporate managers (Chen et al., 2019). Hence, there is an urgent need to investigate the evolutionary game behavior among multiple stakeholders in corporate finance and conduct an in-depth analysis of the sector's current state. An enterprise's financial system primarily encompasses six subsystems: financing, investment, procurement, production, sales, and profits. These subsystems collectively facilitate the financial cycle of fund acquisition, allocation, utilization, recovery, and distribution (Ukko et al., 2019). Figure 1 illustrates the elements involved in the financial analysis of a company within a multi-entity context (Wu & Huang, 2022).

Figure 1 provides clear insight that within a multi-subject perspective, financial analysis encompasses various domains that entail higher levels of risk. Significant interplay and

Figure 1. Financial risk and management



interdependence among different sectors lead to increased complexity. In the case of energy companies, the involved departments primarily focus on environmental protection, subject to frequent policy changes. Hence, considering the accuracy of financial evaluation from a multi-subject aspect becomes crucial (Deng et al., 2020).

Commonly employed statistical regression methods for intelligent evaluation involving multiple factors include linear regression, tree regression, and support vector regression (SVR). These machine learning algorithms are based on convex optimization principles, offering a solid mathematical and theoretical foundation with good interpretability. However, the generalization performance of such methods often falls short when confronted with multiple sources of information, especially in scenarios involving numerous subject sectors (Akbari et al., 2019). In the context of low-carbon initiatives, a critical analysis of the traditional performance evaluation system has exposed certain shortcomings. Studies suggest that when constructing an evaluation system for enterprises, emphasis should be placed on developing low-carbon strategies as a critical objective for future growth. Despite the diminished interpretability resulting from utilizing large volumes of data and black box training methods, deep learning significantly enhances accuracy, enabling the generation of output results at each level based on specific requirements, thereby facilitating high-precision, multi-subject analysis.

The conventional statistical regression methods mentioned above enable intelligent evaluation concerning multiple factors. These methods are based on convex optimization principles and possess an excellent mathematical theoretical foundation and interpretability. However, their generalization performance is often insufficient when dealing with multiple sources of information, particularly in multi-subject sectors. The traditional performance evaluation system has been critically analyzed and investigated in the low-carbon context, revealing some limitations. Therefore, while creating an evaluation system for businesses, studies suggest prioritizing the goal of low-carbon development for future progress. Although learning large amounts of data and black box training may decrease interpretability, deep learning substantially improves accuracy. It delivers output for each level according to specific needs, resulting in high-precision, multi-subject analysis.

This paper addresses energy enterprises' current financial development requirements from a multi-subject perspective. It quantifies data related to each sector through hierarchical quantitative analysis. Subsequently, it conducts a data fusion assessment across different subject levels using the long short-term memory (LSTM) method, thus achieving an intelligent financial performance evaluation of energy enterprises. The paper makes the following specific contributions:

1. The financial contribution of each sector of energy enterprises is quantified using the analytic hierarchy process (AHP) method. Indicators such as the utilization rate of new energy and pollution control efficiency are incorporated into the assessment.
2. Regression analysis of the financial contribution of each department is performed using the LSTM method, followed by the integration of department-specific contribution data to facilitate financial performance evaluation.
3. A practical test is conducted. The test results demonstrate that the model effectively evaluates the contribution of each subject sector and achieves comprehensive analysis accordingly.

The remaining sections of this paper are organized as follows: Section 2 provides an overview of related works on financial performance evaluation. Section 3 introduces the methods employed in this study. Section 4 describes the experimental setup and presents the financial performance evaluation analysis, including the model's application. Section 5 discusses the results and highlights essential considerations in the context of low-carbon transformation.

RELATED WORKS

Using machine learning to evaluate the relationship between finance and low-carbon environmental protection includes data collection, cleaning, feature engineering, model selection and training, model evaluation, model interpretation, deployment, and monitoring. The model can reveal the potential correlation between financial performance and low-carbon environmental protection by analyzing historical data. It can also provide policy recommendations. This helps companies formulate sustainable development strategies and balance economic and environmental goals. In establishing criteria for financial evaluation, scholarly researchers aim to quantify and scrutinize the information and endeavors of diverse departments within an organization, aiming to accomplish the financial assessment amalgamation from multiple abstract dimensions. In the context of corporate performance evaluation, Tseng et al. (2009) curated a comprehensive set of sixteen indicators derived from five facets of manufacturing, constituting the foundation of the evaluative indicator system. These sixteen indicators encompass financial and non-financial performance measures. Focusing on social responsibility, Inoue and Lee (2011) delved into five principal stakeholder concerns related to voluntary company activities: employees, products, community, environment, and diversity. Building upon survey data from seventy Finnish business departments, Kallunki et al. (2011) incorporated the enterprise resource planning department into the evaluative index system, substantiating its efficacy through a demonstrative examination. Zhang and Tan (2012) meticulously selected indicators from four dimensions—finance, customers, business, and innovation—and formulated a rational performance evaluation system tailored specifically for small and medium-sized third-party logistics enterprises. Wang and Han (2021) expounded upon the prospective developments within SMEs and elucidated the significance of cultivating online finance within e-commerce. Li and Zhang (2021) proposed two distinct Internet of Things (IoT) scenarios employing multivariate outlier detection methods to identify a niche domain that exclusively uses RFID data. Rhou et al. (2016) scrutinized the relationship between corporate social responsibility and financial performance through an extensive survey of fifty-three companies, revealing the importance of corporate social responsibility activities for enterprises.

Researchers have endeavored to enhance precision and optimization by incorporating additional evaluation models into methods employed in financial performance assessment. Tung and Lee (2010) sought to amalgamate the merits of gray theory and factor analysis, developing a gray factor analysis (GFA) performance evaluation model through a gray correlation matrix. Analyzing the financial performance of twelve listed real estate companies, Li et al. (2011) selected their third-quarter financial reports from 2010 and employed principal component analysis to evaluate their economic prowess. Bulgurcu (2012) introduced a multi-criteria decision model to measure and compare the financial performance of thirteen technology companies listed on the Istanbul Stock Exchange. Yalcin et al. (2012) proposed a hierarchical economic evaluation model by delineating the primary standards and sub-standards of accounting-based financial performance (AFP) and value-based financial performance (VFP). Wang (2014) evaluated the financial performance of container shipping companies in Taiwan by harnessing the power of fuzzy multi-criteria decision-making (FMCDM) techniques. Shaverdi et al. (2014) adopted fuzzy AHP to assess the financial performance of seven companies within the petrochemical industry.

In the context of low-carbon development within energy companies, their financial evaluations necessitate the consideration of additional low-carbon factors to ensure stable progress. Schultz and Williamson (2011) suggested incorporating the definition of carbon utilization into various economic indicators and scopes, underscoring the importance of analyzing the costs incurred due to climate change, which facilitates the assessment of a company's carbon disclosure level. Burritt et al. (2010) posited that a carbon management accounting framework can comprehensively examine the interplay between financial performance and carbon management. Machine learning methods are increasingly used in financial evaluation to facilitate multi-objective regression analysis. However, the current content of such studies remains relatively rudimentary, failing to adequately delineate the subjects within each company sector, thereby impeding comprehensive hierarchical integration. Given the interconnected nature of the various departments involved in a company's financial evaluation process, it becomes imperative to integrate the performance metrics of multiple departments for thorough analysis.

In the current state of financial evaluation, machine learning techniques are increasingly utilized to achieve multi-objective regression analysis. These methods can significantly reduce the human workload and cover more concepts related to low carbon. However, the content of such studies tends to be rather basic and fails to delineate the subjects of each sector within the company to accomplish a hierarchical integration. From the perspective of multiple subjects in the financial evaluation process of a company, single departments cannot be considered independently from the others. Therefore, the analysis must integrate the performance of multiple departments. In the context of energy enterprises' green development, it becomes necessary to consider additional factors in financial evaluations, integrate information from other departments, and incorporate low-carbon elements in multiple integration decisions to accomplish a more comprehensive economic evaluation and all-around assessment of the company's current situation.

ESTABLISHMENT OF A FINANCIAL PERFORMANCE EVALUATION SYSTEM FOR ENERGY ENTERPRISES

AHP for the Evaluation Index Quantification

The financial evaluation analysis conducted in this paper is influenced by multiple subject subsystems, as depicted in Figure 1, wherein the content is segmented into various subjects. The financial evaluation is categorized into six distinct subsystems, each influenced by many information sources, necessitating a gradual quantification process. To address this requirement, the present study employs the AHP method for relevant quantification (Yu et al., 2021). AHP is suitable for dealing with multi-dimensional decision-making problems and can effectively integrate information from various dimensions. Secondly, it can transform subjective information into quantifiable results, helping to reduce uncertainty in decision-making. In addition, the hierarchical structure and consistency check of AHP make decisions clearer and more credible, improving the quality and transparency of decisions. Most importantly, AHP has broad applicability and can be used for various multi-criteria decision-making problems, providing decision-makers with powerful tools to handle complex decision-making situations.

Firstly, the judgment matrix shown in Equation 1 is constructed by weight replication, where C_{ij} is the scoring system for the importance of elements i and j relative to the upper target, and n represents the number of elements. This matrix must be normalized after its establishment to guarantee that it is a positive definite matrix and that the diagonal elements on its matrix are reciprocal:

$$C = (C_{ij})_{n\times n} \tag{1}$$

After the matrix is built and calculated, the product of each row of the matrix M_i and its square root $\overline{W_i}$ is calculated, as shown in Equation 2:

$$\overline{W_i} = n\sqrt{M_i} \tag{2}$$

The weight of each level can be obtained by vector normalization using Equation 3:

$$W = \frac{\overline{W_i}}{\sum_{j=1}^{n} \overline{W_j}} \tag{3}$$

Before calculating the weights, it is necessary to calculate the maximum eigenvalue of the verification feature matrix into consistency indicators and then set the weights to obtain the composite score Y, where Y_i is the indicator score and n is the number of indicators:

$$Y = \sum_{i=1}^{n} W_i Y_i \tag{4}$$

By employing the above calculation method, the contents of different subjects can be further delineated, allowing for the quantification of specific details within each subject, such as investment efficiency, innovation ability, and more. The refined indicators from each stratum can then be integrated into the evaluation model, facilitating the comprehensive quantitative analysis of the financial evaluation index system.

LSTM for the Financial Performance Evaluation

LSTM, a type of recurrent neural network (RNN), is a well-suited approach for addressing and predicting intricate problems. LSTM mitigates the limitations of traditional RNNs by incorporating the state variable C alongside the existing neurons and skillfully introducing controllable self-loops. This design allows sustained gradient flow over extended periods, facilitating the sequential transfer of memory information. Figure 2 visually represents the unfolded network structure (Yu et al., 2019).

In Figure 2, at moment t, the current neuron has three inputs: the current moment input Xt, the previous output t−1, and the previous memory state t−1. The critical point that makes LSTM better than RNN is its ability to control state C so that the gradient can flow sustainably for a long time, thus transferring the memory information from the initial position to the end position. Figure 3 shows the structure of the long-term state C control gate.

In Figure 3, C is the long-term state and represents the control gate, which includes three switching gates: the forget gate, the input gate, and the output gate. The equation for the forget gate is represented by Equation 5, which controls how much information is discarded or preserved in the previous memory:

Figure 2. Structure of the LSTM sequence

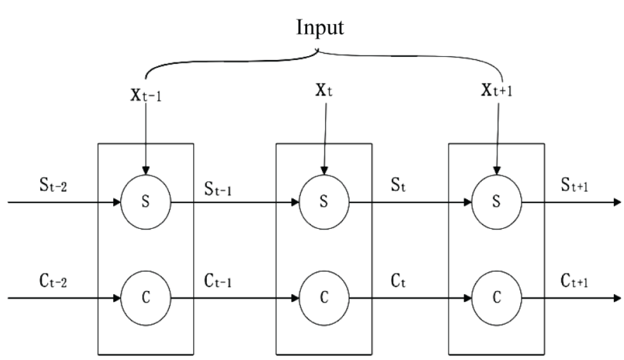
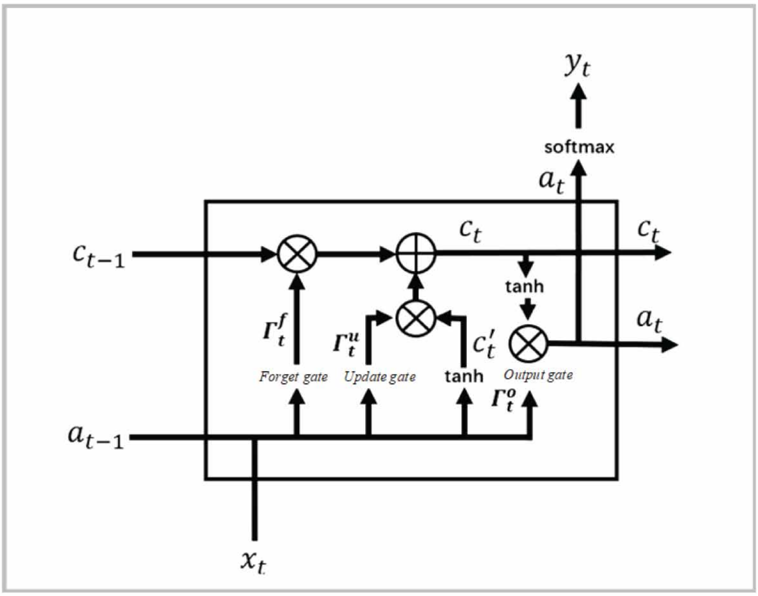


Figure 3. The structure of the LSTM cell



$$f_t = \sigma\left(w_f^T s_{t-1} + u_f^T x_t + b_f\right) \tag{5}$$

Equations 6–8 can be used to calculate the input gate and the updated memory state:

$$i_t = \sigma\left(w_i^T s_{t-1} + u_i^T x_t + b_i\right) \tag{6}$$

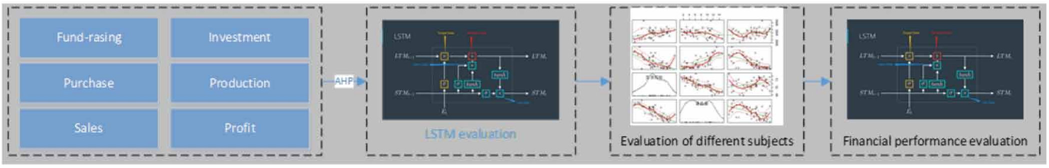
$$c_t^{'} = \tanh\left(w_c^T s_{t-1} + u_c^T x_t + b_c\right) \tag{7}$$

$$c_t = f_t c_{t-1} + i_t c_t^{'} \tag{8}$$

The input gate can be implemented by using Equation 7 to determine how much of the information x_t is added to the memory stream at the current moment. The memory state c_t is implemented using Equation 8. It can be found from the equations that the state can realize selective propagation in the sequence to ensure the accuracy of information.

Figure 4 illustrates the flow of the multi-agent financial evaluation system, which incorporates both the AHP and LSTM methods. The diagram showcases the interconnections and contributions of each subject department within the evaluation framework.

Figure 4. Framework for the financial performance evaluation



EXPERIMENTAL RESULTS AND ANALYSIS

To maintain data integrity and consistency, the expert scores were normalized in this study. Additionally, to prevent any loss of accuracy in fractional calculations, the scores were expanded by a factor of 100. This means the standard score for each stage was set at 100, ensuring consistency throughout the analysis. Moreover, this study considered the enterprises' inherent characteristics during the index quantification. Specifically, it incorporated low-carbon indicators into the evaluation system across the various departments. The paper considered several key low-carbon indicators: carbon emissions, low-carbon policy learning effectiveness, new energy sources' utilization rate, and other indicators related to low-carbon capabilities.

Comparison of Models

This research applied the algorithm framework depicted in Figure 4 to the financial data of energy enterprises in the specified region and relevant research data. The economic data were categorized based on the six subjects presented in the figure, and experts conducted AHP quantitative scoring to process the data. The proposed model was trained using historical enterprise data, and the first layer of prediction results, derived from the utilization of data from the preceding two years, is illustrated in Figure 5.

Figure 5 depicts the prediction results for the six types of subject data using different methods. The figure highlights that the selected model exhibits superior recognition outcomes. To illustrate the disparity between the methods, this paper calculated the absolute error between the expert evaluation results and the machine learning prediction results for comparison. The findings are presented in Figure 6.

In the analysis, the comprehensive explanation presented in Figure 6 provides an overview of the absolute errors, an integral part of evaluating these methods. By carefully considering how the different methods perform across various sectors, this graph illustrates how well they match the complexities of each industry. The LSTM method stands out for consistently aligning

Figure 5. The evaluation results for different prediction methods

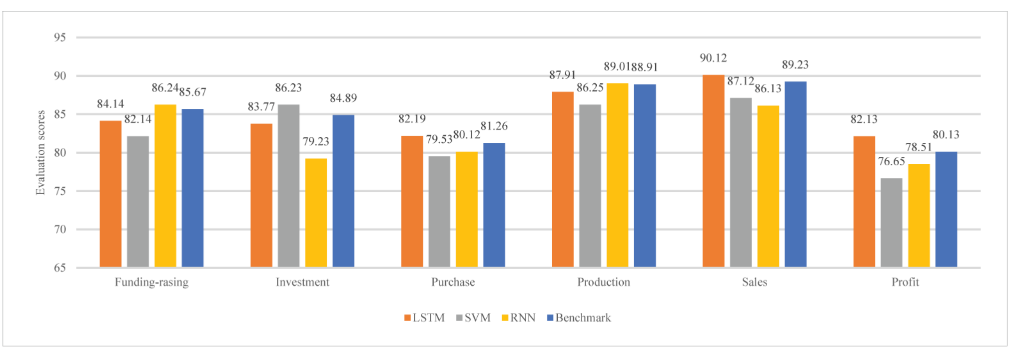
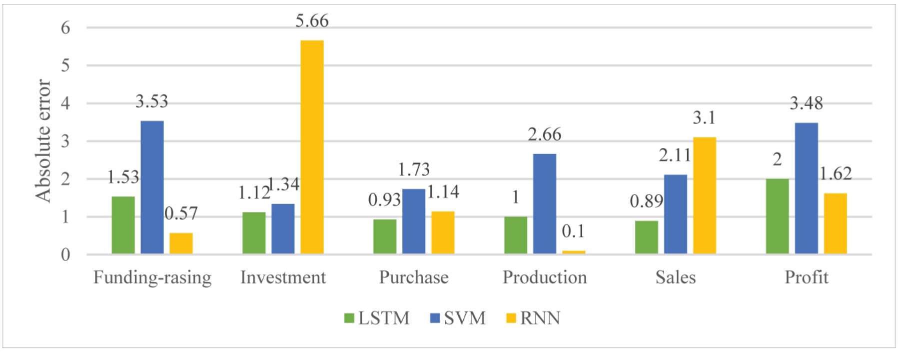


Figure 6. The absolute error of different methods



well with real-world observations. It effectively avoids extreme values, resulting in smoother and more consistent outcomes.

In contrast, the RNN method, despite its potential, showed less consistent results. While the RNN method achieved good performance scores in specific sectors, its underlying instability decreased its overall efficacy. Notably, it showed apparent deviations in the investment sector, suggesting that the method is less reliable and may not provide consistent outcomes.

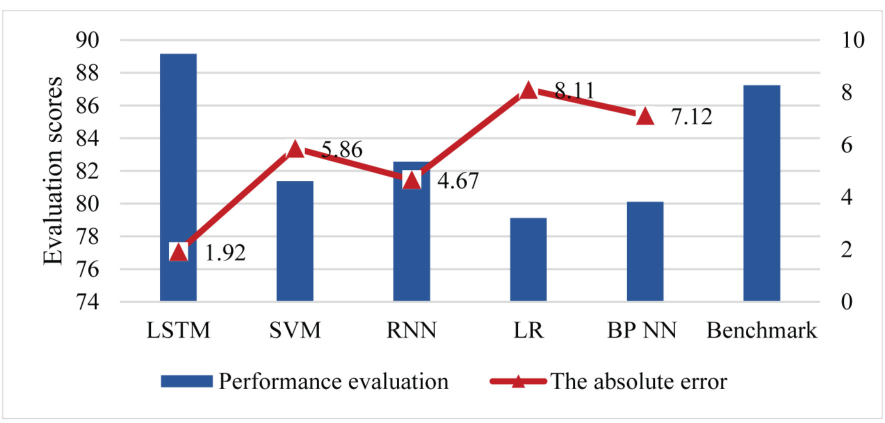
Another limitation emerged related to the RNN method's tendency to struggle with extreme values in practical applications. While not making it impossible to work with, this limitation makes the method less suitable for broader evaluation needs.

Evaluation of the Financial Performance

To achieve the objective of financial performance evaluation, this paper conducted performance assessments for each department in the first layer, followed by the final performance evaluation using the LSTM model. To substantiate the superiority of the proposed model, a multi-class approach was employed for the financial performance evaluation, and the comparative results are presented in Figure 7.

Figure 7 compares the outcomes of the different methodologies. The graph uses the absolute error metric as its basis, making the analysis intuitively easier to understand. In addition, a dashed line

Figure 7. The financial performance evaluation among different methods



shows the distribution pattern of the absolute errors. This use of graphical elements shows the results clearly, allowing for a nuanced understanding of the comparative merits of the different methods.

The superiority of the LSTM method in making predictions is based on its ability to understand change over time. Looking at the results in terms of absolute error underscores the method's usefulness, highlighting its position at the forefront of analytical methods that can help researchers understand information in new ways.

Practical Test

To assess the accuracy of the established model, a practical test was conducted using data from an energy enterprise for the most recent year. Relevant experts were engaged to provide scores for comparison. The overall testing framework is illustrated in Figure 8.

The relevant data was initially quantified during the test using the AHP method. Subsequently, experts assigned scores to each item based on departmental classification and compared them with the model's results. Additionally, the experts completed an overall financial performance evaluation score, enabling a comprehensive data comparison. Figure 9 compares the expert scoring results and the model's calculation results. A meticulously structured methodology was employed throughout the testing phase to distill and quantify the pertinent data. Initially, the AHP method was used judiciously, serving as the basis for quantifying the data points. This methodological approach ensured a rigorous and systematic data preparation stage.

After this, an assembly of experts in their respective fields imputed scores to each data item. Based on a granular departmental classification scheme, these scores were then compared to the computational outputs generated by the model under investigation. This exercise culminated in a comprehensive comparative analysis, comparing the expert-derived scores and model-generated results. At the same time, the experts carried out a thorough evaluation of the overall financial performance. Based on the nuanced insights and judgment of the experts, this approach gave an overarching perspective that enriched the data comparison.

The data were carefully examined to assess the model's performance thoroughly. The absolute errors were calculated, as depicted in Figure 9. In the graph, the dashed lines show how much error exists in the model proposed in this paper. Notably, great care was taken to control and handle these errors during the analysis, underscoring the meticulousness of the experimental design.

When looking at the results, it becomes evident that the sales component is somewhat different than expected; however, this divergence is well within the tolerable limits and is thus acceptable in the larger context. After integrating the findings from the first analysis, calculations were performed to get an overall evaluation of financial performance.

Through a thorough evaluation process, the experts gave the subject an evaluation score of 83.21. At the same time, the LSTM model, known for its aptitude with temporal dependencies, received

Figure 8. The framework for the actual test

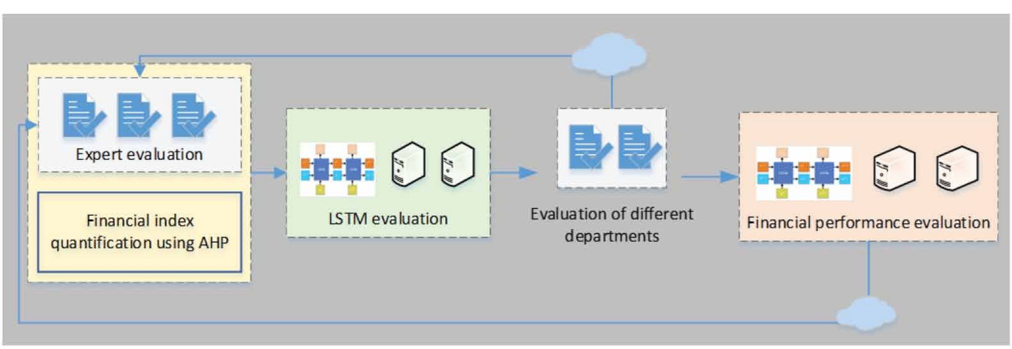
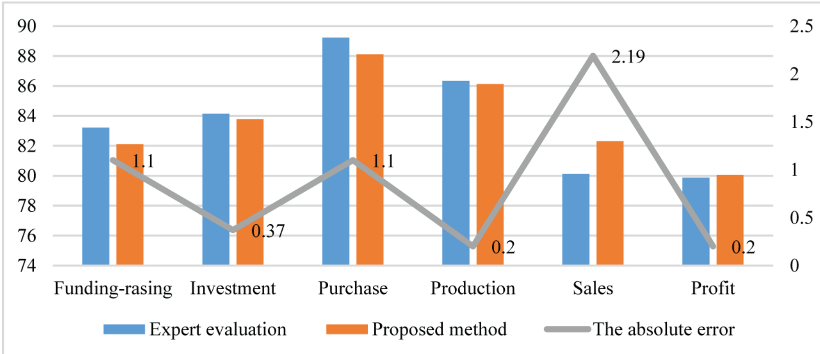


Figure 9. The evaluation results of the different departments



an evaluation score of 81.79. The absolute error between the two scores was only 1.42. Regarding relative significance, this represents only a 1.7% deviation from the expected values.

After a careful and thorough analysis, it can be concluded that the proposed LSTM two-layer evaluation model efficiently assesses performance across various departments. The calculated error rate based on real-world testing was consistently below 2%, thus proving the model's skill in meeting the demanding performance evaluation requirements. All of this evidence strongly supports the idea that the model is highly accurate and capable of handling the complex needs of performance assessment.

DISCUSSION

This paper has successfully established a financial performance evaluation system tailored to energy enterprises. A multi-layer analysis method was employed in the algorithm design process to comprehensively analyze the interrelationships among various sectors. Diverging from traditional multi-objective regression prediction evaluation research, the method devised in this paper eschews direct regression and instead employs hierarchical regression, thereby enhancing interpretability. In the first level of output, further analysis can be conducted using the weights assigned to different sectors, allowing strategic sectors of the enterprise to access more detailed information (Smagulova & James, 2019).

Additionally, the utilization of LSTM in this paper proves advantageous in evaluating the historical data of each sector, owing to its exceptional temporal memory capabilities. This, in turn, provides certain advantages for future prediction. Compared to traditional regression-based and machine-learning methods, deep learning methods, including LSTM, have garnered significant attention in multi-objective regression analysis due to their effectiveness in processing nonlinear data (Dong et al., 2019). LSTM excels at uncovering correlations within historical data, and its merits in subsequent evaluation have been validated through experimental analysis. Therefore, this paper's proposed multi-layer classification regression model yields robust and effective predictive evaluation outcomes.

In the future development of energy enterprises, aligning with the low-carbon trend is crucial. An evaluation system based on the low-carbon economy has been established, enabling the assessment of financial and business performance and analyzing the level of low-carbon development within the enterprise. The following aspects should be considered when applying the financial evaluation system in a low-carbon context (Masharsky et al., 2018):

1. **Focus on improving asset utilization efficiency (Gay & Sinha, 2013):** Instead of solely emphasizing the increase in total asset turnover rate by reducing the overall amount of assets, it is essential to concentrate on enhancing asset utilization efficiency. Striving to achieve more significant economic benefits with the least amount of total assets is critical.

2. **Strengthen cost and expense control (Gonzalez et al., 2021):** Enterprises should reinforce control over costs and various expenses while pursuing enhanced economic benefits. It is essential to ensure that expense growth remains within a specific range, not surpassing the increase in operating income. Conscious efforts should be made to save costs in employee management and other areas.
3. **Optimize the capital structure to reduce financing costs (Ramli et al., 2019):** Enterprises should establish development strategy objectives that limit the organization's debt level to a reasonable range. Simultaneously, continuous optimization of the capital structure is necessary, utilizing financial costs and revenues to reduce the financial risks faced by the enterprise. This approach fosters sustainable development.
4. **Actively increase investment and financing in low-carbon projects (Sun et al., 2020):** Enterprises should gradually focus on developing low-carbon projects in future investments and financing. This enables long-term benefits and garners strong government and community support in funding, thereby enhancing the enterprise's low-carbon competitiveness.

By adhering to these principles, energy enterprises can navigate the path toward sustainable development while effectively addressing the challenges and opportunities the low-carbon economy presents.

CONCLUSION

This paper has investigated the intelligent analysis requirements for financial performance. It proposed a layered and integrated economic evaluation method inspired by analyzing a multi-subject perspective, specifically in energy enterprises' financial performance evaluation system. The LSTM method was utilized to assess the performance of various finance-related departments, followed by an overall performance evaluation completed by the second layer model prediction. In the actual test, the proposed two-layer evaluation method had an error rate of only 1.7% compared with the expert evaluation, proving its effectiveness in achieving energy enterprises' financial performance evaluation task. Additionally, the hierarchical fusion method dramatically improves the model's interpretability, enabling the decision-making department to further analyze different subjects' contributions. The model provides technical support for the financial evaluation of energy enterprises and offers novel ideas for the future development of low-carbon industries.

Nonetheless, the distinct subject sectors examined in this study were assumed to be relatively self-contained, and the model neglected to account for their interconnectedness. The system should assess the correlation between subjects in future research by incorporating metrics such as correlation coefficients. Additionally, energy enterprises should invest in green development and low-carbon policies to facilitate their strategic transformation.

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COMPETING INTERESTS

The author of this publication declares there are no competing interests.

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