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Variational Autoencoder-based High-dimensional Feature Extraction for Economic Analysis of Power Cost Data

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The purpose of this paper is to extract the characteristics of power cost data using a deep learning model and to evaluate and predict the cost structure, profitability, and future development trends of power enterprises by combining economic analysis methods. Firstly, the paper innovatively employs a Variational Autoencoder for feature extraction. This model extracts low-dimensional latent representations of the data through an encoder and reconstructs the data through a decoder, retaining key structural information. The dataset used here consists of 1,800 records, which include costs, revenues, output, and energy consumption data from power companies, covering multiple enterprises and time periods. Secondly, during the model training process, optimization is performed with a learning rate of 0.001, a batch size of 64, and 50 training epochs. Performance comparisons under different hyperparameter combinations indicate that the model with 256 hidden nodes in both the encoder and decoder layers yields the best performance. Lastly, economic analysis methods, such as cost-benefit analysis and economic forecasting, are applied to assess and predict the profitability and future trends of the power companies. The specific results show that the reconstruction error of this model is 0.032, and the KL divergence is 0.006. In terms of refined economic analysis, the net profit predicted by the model reaches 5.36 million yuan, with a prediction accuracy of 93.5%. In terms of robustness, although the prediction accuracy fluctuates slightly, it remains high overall, and both the training time and prediction time show stability. Moreover, testing on multiple datasets from sources such as University of California, Irvine, Kaggle, and government open data platforms shows that the model's prediction accuracy remains between 92.3% and 94.2%, with stable training and prediction times, demonstrating its strong generalization ability. The proposed model offers several advantages. Overall, this paper presents a novel approach and method for economic analysis and decision-making in power enterprises, which holds significant practical value.

Povzetek: Opisana je inovativna uporaba variacijskega avtomatskega kodirnika za ekstrakcijo lastnosti stroškov električne energije, ki omogoča poglobljeno ekonomsko analizo in napovedovanje dobičkonosnosti podjetij.

1 Introduction

Under the current social background, as one of the pillar sectors of the national economy, plays a crucial role in national economic development. Therefore, its operating efficiency and cost control are of significant importance. Power cost data forms a critical foundation for cost management in the electricity industry, encompassing information such as company costs, revenues, output, and energy consumption. This data plays a significant role in evaluating the economic performance of power companies [1]. However, traditional statistical methods and empirical models struggle to handle high-dimensional features and complex relationships. These methods often rely on expert experience for feature selection, which lacks automation and efficiency. As a result, leveraging advanced deep learning technologies to extract key features from power cost data and enhance the efficiency and accuracy of analysis has become a key focus of current research [2]. Therefore, the use of advanced data analysis technologies to improve the efficiency and accuracy of power cost data analysis has become an urgent issue that needs to be addressed.

In recent years, the rapid development of deep learning technology has brought about revolutionary changes, with its application expanding across various fields, including the power industry [3]. With its unique advantages, deep learning enables the automatic learning and representation of data features by constructing a multi-level neural network structure. This capability of automatic learning allows deep learning to conduct data analysis and pattern recognition efficiently, without human intervention [4]. The Variational Autoencoder (VAE), a deep learning model, is capable of automatically learning the latent representations of data. By constructing an encoder and a decoder, it compresses the data while preserving its essential information. This approach is particularly well-suited for feature extraction and pattern recognition in high-dimensional data [5]. Power cost data, which includes information such as company costs, revenues, output, and energy consumption, plays a crucial role in evaluating the economic performance of power companies [6]. Deep learning models can effectively handle such data and enable a more in-depth and comprehensive analysis by learning multi-level representations of the data [7]. Therefore, the application of deep learning frameworks in power cost data analysis can not only improve the accuracy and efficiency of data analysis but also provide more intelligent and comprehensive data support for the power industry.

The primary objective of this paper is to enhance the feature extraction capability of power cost data and improve its predictive accuracy in economic analysis, thereby supporting more precise cost management and decision-making. Although existing deep learning methods have achieved certain results in the power industry, they still exhibit the following limitations: (1) Traditional autoencoders (AEs) tend to lose critical information during the data compression process, resulting in insufficient feature extraction capability; (2) Existing economic forecasting models rely on manual feature selection, making it difficult to adapt to the complexity and high-dimensional nature of the data; (3) Deep learning models face challenges such as high computational costs and limited generalization ability when modeling high-dimensional data.

To address these limitations, this paper adopts two improvement strategies: (1) Regularizing the latent variable distribution by using Kullback-Leibler (KL) divergence constraints to stabilize the distribution of the latent space, enhancing the continuity and robustness of data representation; (2) Introducing a multilayer perceptron structure to optimize the decoder, improving feature reconstruction ability and reducing information loss. Experimental results show that the improved method achieves superior feature extraction performance in terms of reconstruction error and KL divergence, providing more accurate and efficient input for subsequent economic analysis. By designing and implementing the feature extraction method based on VAE, the complex features of power cost data can be captured more accurately, providing a more reliable and effective data foundation for subsequent economic analysis.

This paper employs a VAE to extract latent features from power cost data and optimizes the model using the best hyperparameters. Cost-benefit analysis (CBA) is integrated to assess the profitability of power enterprises, while economic forecasting methods are applied to predict future cost trends. Through experimental comparisons, the performance of the proposed model is evaluated against AEs, convolutional neural networks (CNNs), recurrent neural networks (RNNs), and support vector machines (SVMs) in terms of reconstruction error, KL divergence, prediction accuracy, and computational efficiency. CBA is used to evaluate the profitability of power enterprises and analyze the impact of various cost components on overall power costs. Additionally, economic forecasting methods are employed to construct a predictive model based on feature extraction, forecasting future trends in cost structure. Experimental results demonstrate that the proposed model outperforms other methods in terms of reconstruction error, KL divergence, and prediction accuracy, maintaining stable performance across multiple datasets (University of California, Irvine (UCI), Kaggle, and government datasets), which confirms its strong generalization ability. This paper aims to explore the application of deep learning frameworks in the analysis of power cost data and proposes a VAE-based feature extraction method to enhance the accuracy and intelligence of economic analysis in power enterprises. The findings provide more accurate and efficient decision support for cost management and economic forecasting in the power industry. The applicability of this method is not limited to a specific power cost dataset. In experiments, the method was tested on various datasets (UCI, Kaggle, and government data), with the results showing high prediction accuracy (92.3%-94.2%) across different data sources. Moreover, this approach is not only applicable to power cost data but can also be extended to other high-dimensional economic data analysis tasks, such as energy price forecasting and corporate financial analysis. Due to the high-dimensional latent space representation in VAE, its computational complexity is higher than that of traditional regression methods. During the training phase, as the data size increases, the demand for computational resources also increases. Therefore, for large-scale datasets, further optimization of computational efficiency (e.g., distributed computing or dimensionality reduction techniques) will be necessary. Additionally, the latent space structure of VAE requires further optimization to enhance its generalization ability across various domains. Future research may focus on improving computational efficiency and extending the cross-industry applicability of the model.

2 Literature review

In previous research, many scholars have conducted in-depth discussions on the cost management of the power industry [8, 9]. For example, the study by Fu et al. found that the costs in the power industry were mainly concentrated in fuel costs, equipment maintenance costs, and labor costs, with fuel costs being the primary factor affecting the profitability of power enterprises [10]. Additionally, some scholars have attempted to use economic models for the economic analysis of the power industry [11, 12]. For instance, the research by de Oliveira and Bollen showed that the level of economic growth had a significant impact on the growth of power demand, which provided important insights for capacity planning and resource allocation in the power industry [13]. In addition to the traditional methods mentioned above, recent studies have explored the use of machine learning and data mining technologies for cost management and economic analysis in the power industry [14, 15]. For example, Yoo et al. used a neural network model to predict the costs of electric power enterprises and achieved promising prediction results. Their research demonstrated that machine learning models could effectively uncover patterns in power industry data, offering new approaches and methods for economic decision-making in power enterprises [16].

In the field of data analysis, deep learning technology has become a powerful tool [17, 18]. For instance, Saha et al. employed deep learning models to forecast financial market data, achieving promising results. Their study demonstrated that deep learning models could effectively capture the complex dynamics of financial markets, providing investors with more accurate predictions and better decision-making support [19]. In recent years, researchers have begun combining deep learning with statistical models for cost management and economic analysis in the power industry. For example, Khalid et al. proposed a deep feature extraction-based fault detection method for power systems [20]. This method has demonstrated strong generalization ability in complex energy systems [21]. Additionally, Pei et al. employed the knowledge-assisted neural-convolutional neural network structure for power load forecasting, improving prediction accuracy while reducing computational complexity [22]. Beyond financial and economic fields, deep learning technologies have been widely applied to data analysis and forecasting in other domains such as healthcare, transportation, and more [23-25].

The comparison of studies related to cost management and economic forecasting in the power industry is presented in Table 1 below:

Table 1: Studies on cost management and economic forecasting in the power industry

Study	Method	Dataset	Key Indicator	Main Strengths and Weaknesses
Fu et al. [10]	Traditional Cost Analysis	Industry Report Data	Identification of Cost Structure	Clear structure, but challenging to handle large-scale data
de Oliveira & Bollen [13]	Linear Regression	National Power Data	Demand Forecast Accuracy 80%	Applicable only to simple relationships, struggles to capture nonlinear features
Yoo et al. [16]	Neural Networks	Internal Power Company Data	Prediction Error 12%	Capable of automatic feature learning, but prone to overfitting
Pei et al. [22]	Deep Learning	Macroeconomic Data	Prediction Error 8%	Can capture temporal relationships, but high computational cost

Based on the above research, traditional cost management and economic analysis methods have made some progress in the power industry, but they still face limitations, such as an inability to handle complex data characteristics effectively. In recent years, the emergence of machine learning and deep learning technologies has provided new solutions for the power industry, enabling a better exploration of underlying data patterns and improving the accuracy and efficiency of analysis. However, deep learning technologies also face challenges, such as weak model interpretability and high data demands. The improved VAE proposed here enhances feature extraction capability by regularizing latent variables and optimizing the decoder with a Multi-Layer Perceptron (MLP), making the predictions more accurate and interpretable in conjunction with economic analysis methods.

3 High-dimensional feature extraction and refined economic analysis of power cost data

3.1 Data collection and preprocessing

This paper utilizes power cost data from a city's power engineering cost information network in mainland China. The dataset includes information on the costs, revenues, outputs, and other variables from several power enterprises over a specific period. It covers a range of power enterprises of varying sizes, providing a diverse set of data. Specifically, the dataset includes the following categories:

- Cost data: including fuel costs, equipment maintenance costs, labor costs, etc.
- Revenue data: including power sales revenue, government subsidies, etc.
- Output data: including power output, utilization rates of power generation equipment, etc.
- Energy consumption data: including fuel consumption and electricity consumption [26].

The dataset contains approximately 1,800 records, with each record corresponding to the cost, revenue, output, and energy consumption of a particular power enterprise during a specific time period. This dataset spans multiple power enterprises across different time points, ensuring both temporal diversity and enterprise variability, which enhances the model's generalization ability.

Before using the data for analysis, a series of preprocessing steps are carried out to ensure the quality and suitability of the data. The preprocessing process includes the following steps:

Data Cleaning: Missing and abnormal values are removed to ensure the integrity and accuracy of the data [27].

Data Conversion: The data is normalized or standardized so that different features are on the same scale [28].

Dataset Division: The dataset is split into a training set, validation set, and test set (in a 7:2:1 ratio) for model training and evaluation.

In the data preprocessing stage, this paper employs K-Nearest Neighbors interpolation to handle missing values, aiming to retain as much data integrity as possible. For outlier detection, Z-score normalization is applied to filter data points that exceed three standard deviations from the mean. Additionally, Local Outlier Factor is used to remove anomalous samples. Furthermore, min-max normalization is applied to numerical variables, scaling them to the [0, 1] range to ensure consistent feature scales, which in turn improves the model's convergence speed.

3.2 Selection and design of deep learning model

In this paper, the VAE is chosen as the deep learning model for feature extraction from power cost data [29]. The VAE is a generative model, and its core idea is to achieve compressed representation and data generation by learning the underlying distribution of the data. The model primarily consists of two components: the encoder and the decoder. The encoder's function is to map the input data to the distribution parameters in the latent space [30]. Specifically, the encoder transforms the original power cost data into distributional features within the latent space, which effectively capture the essential information and structural characteristics of the original data [31, 32].

Specifically, when selecting the deep learning model, the VAE offers several advantages: First, compared to generative adversarial networks (GANs), VAE demonstrates greater stability in data feature extraction, avoiding the instability associated with adversarial training. This results in a more controllable distribution in the latent space. Second, in contrast to Transformer-based AEs, VAE exhibits higher feature extraction efficiency and lower computational complexity when handling high-dimensional structured data, while better preserving the consistency of the data distribution. Furthermore, VAE is particularly well-suited for high-dimensional power cost data, as its latent variable regularization mechanism reduces information loss during the dimensionality reduction process, thereby enhancing the stability of economic predictions. For these reasons, VAE is chosen in this paper to improve the high-dimensional feature learning capability of power cost data.

The workflow of the VAE model is as follows: First, the encoder maps the original power cost data to the distribution characteristics in the latent space. Then, samples are drawn from random variables in the latent space, and the decoder converts these samples into data. Finally, by comparing the generated data samples with the original data, the model's parameters are optimized to minimize the difference between the generated and original data [33]. The main structure of the VAE is shown in Figure 1.

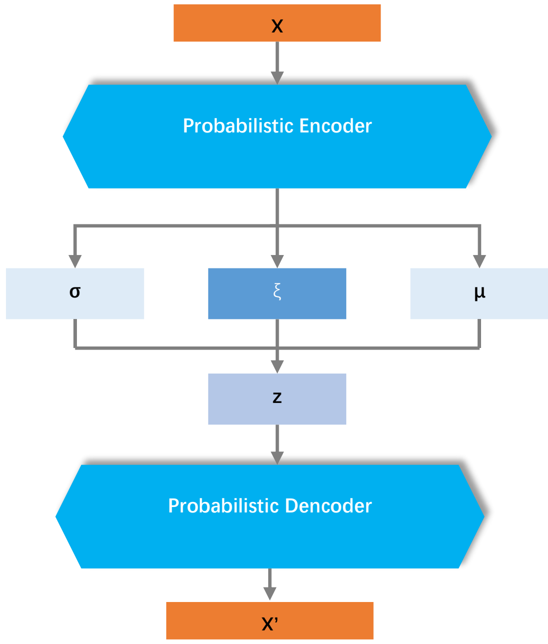

Figure 1: VAE structure.

This characteristic of the VAE provides significant advantages for feature extraction from power cost data. First, VAE can learn the latent distribution of the data, not just its surface features, which is useful for extracting advanced features and structural information. Second, since the data samples generated by VAE are random, diverse data samples can be produced, improving the robustness and generalization ability of the model [34]. Lastly, the structure of the VAE encoder and decoder is relatively simple, yielding good training results, which makes it suitable for large-scale data processing and feature extraction.

Traditional data analysis methods encounter difficulties in capturing nonlinear structures when processing high-dimensional data. In contrast, the VAE enhances data representation through probabilistic modeling, enabling dimensionality reduction while preserving complex structural features. The theoretical foundation of this paper is based on two key aspects. First, variational inference allows the VAE to approximate the true data distribution, facilitating stable learning of high-dimensional latent representations. Second, the information bottleneck principle is applied, where the VAE employs KL divergence constraints to eliminate redundant information and retain only the most predictive features. In economic data analysis, compared to traditional methods such as principal component analysis (PCA), VAE effectively captures temporal dependencies and models long-term economic trends through latent variable representations, making it particularly advantageous for analyzing power cost data.

In this paper, the VAE is employed to learn latent representations of power cost data and extract high-dimensional features for refined economic analysis. To accommodate the complex structure of power industry data, the VAE is designed as follows:

1. Input Data

The input variable x consists of key economic indicators of power enterprises, including cost, revenue, production output, and energy consumption. Each record represents a specific enterprise's data for a given time period.

2. Encoder

The encoder is a three-layer fully connected network with hidden dimensions of 256 → 128 → 64. The Rectified Linear Unit activation function enhances nonlinear representation capability. The encoder maps the input data to the mean (μ) and variance (σ^2) of the latent space distribution:

$$\mu, \sigma^2 = \text{ Encoder } (x) \tag{1}$$

Reparameterization Trick: To enable efficient gradient propagation, the latent variable z is computed using the reparameterization trick:

$$z = \mu + \sigma \cdot \epsilon, \epsilon \sim \mathcal{N}(0, I) \tag{2}$$

In Equation (2), ϵ is sampled from a standard normal distribution to maintain differentiability. The VAE ensures that the latent variable z follows a standard normal distribution$p(z)\sim N(0,I)$, providing the following advantages:

- Continuity: Small changes in the latent space lead to smooth variations in the data space, ensuring stable and coherent data representations.
- Operability: The consistency of latent variables across samples facilitates high-quality sample generation.
- Efficient Data Compression: The model compresses data while minimizing reconstruction error, preserving essential features for economic analysis.

3. Latent Space Features

In the latent space, each data point is mapped to a low-dimensional vector z, which encapsulates its core characteristics. This representation facilitates pattern recognition in power cost data, enabling deeper insights into cost structures and profitability models across enterprises.

4. Decoder

The decoder mirrors the encoder's architecture, with hidden layers configured as 64 → 128 → 256. It reconstructs the original input x from the latent variable z using a MLP:

$$\hat{x} = f_{\text{decoder}}(z) \tag{3}$$

In Equation (3), z is a stochastic variable sampled from the latent space. The reconstructed output $\hat{x}$ is then compared with the original input x to minimize reconstruction error.

The VAE optimization objective is to minimize the weighted sum of reconstruction loss and KL divergence, ensuring both data fidelity and a well-structured latent space. The objective function is formulated as Equation (4):

$$\mathcal{L} = \frac{1}{N}\sum_{i=1}^{N} \left(L_{recon}(x_i, \hat{x}_i) + \beta L_{KL}(\mu_i, \sigma_i^2) \right) \tag{4}$$

In Equation (4), N is the number of training samples, x_i is the i-th input, and $\hat{x}_i$ is its reconstructed counterpart. The encoder outputs the mean μ_i and σ_i^2 of the latent variables.

The reconstruction loss $L_{recon}(x_i, \hat{x}_i)$ measures the difference between the original and reconstructed data, typically using Mean Squared Error (MSE):

$$L_{recon}(x_i, \hat{x}_i) = \|x_i - \hat{x}_i\|^2 \tag{5}$$

The KL divergence $L_{KL}(\mu_i, \sigma_i^2)$ regularizes the latent space by minimizing the divergence between the learned latent distribution $q(z|x)$ and the standard normal prior $p(z)=N(0,I)$:

$$\mathcal{L}_{KL} = -\frac{1}{2}\sum_{j=1}^{d} \left(1 + \log\, \sigma_{i,j}^2 - \mu_{i,j}^2 - \sigma_{i,j}^2\right) \tag{6}$$

In Equation (6), d denotes the latent space dimensionality, and $\mu_{i,j}$ and $\sigma_{i,j}{}^2$ represent the mean and variance of the latent variable in the j-th dimension. The KL divergence regularizes the latent space distribution to align with a standard normal distribution, preventing overfitting and ensuring a smooth latent representation.

The hyperparameter β controls the trade-off between reconstruction accuracy and latent space regularization in the β-VAE framework:

- β>1 enforces stronger regularization, improving feature disentanglement.
- β<1 prioritizes reconstruction quality, making it more suitable for complex datasets.

After completing model training, the performance of the VAE is evaluated using the validation set and test set. The evaluation primarily focuses on the model's reconstruction ability, the continuity of the latent space, and the effectiveness of feature extraction in power cost data analysis. Additionally, model performance under different parameter and hyperparameter settings is compared to determine the optimal configuration. To optimize the VAE model, this paper employs Bayesian optimization for hyperparameter tuning. Compared to traditional grid search and random search, Bayesian optimization efficiently identifies optimal hyperparameter configurations with fewer evaluations. It leverages Gaussian Process Regression (GPR) to model the hyperparameter space and selects the best set of parameters in each iteration based on the Expected Improvement (EI) criterion. The optimization process consists of the following steps:

(1) Definition of the Hyperparameter Search Space: The paper considers the following hyperparameters for optimization:

- Number of hidden units in the encoder: {128, 256}

- Number of hidden units in the decoder: {128, 256}
- Learning rate: {0.0005, 0.001}
- Batch size: {32, 64}
- Number of training epochs: {30, 50}

(2) Initial Exploration: Twenty sets of hyperparameters are randomly selected and evaluated based on reconstruction error and KL divergence.

(3) Bayesian Optimization Iterations:

- GPR models the relationship between hyperparameters and model performance.
- EI criterion identifies the hyperparameter combination most likely to enhance the loss function.
- The VAE is trained with the selected parameters, and performance metrics are recorded.
- The GPR model is updated iteratively, and the process repeats for 50 optimization rounds.

(4) Selection of the Optimal Hyperparameter Configuration: After completing Bayesian optimization, the best-performing hyperparameter set is chosen for the final VAE model.

This approach ensures efficient exploration of the hyperparameter space, leading to improved model performance in power cost data analysis.

3.3 Refined economic analysis method

The trained VAE model is utilized to extract high-dimensional features from power cost data. Specifically, the encoder maps the original data into the latent space, and the mean vector in this space serves as the feature representation of the data. This feature extraction method effectively preserves critical information while simultaneously achieving dimensionality reduction and data compression. By leveraging the learned latent representations, the refined economic analysis can identify underlying patterns in power cost structures, improve predictive accuracy, and enhance decision-making in power enterprise management.

The decision to use the mean vector (μ) as the feature representation in the VAE for economic analysis tasks is based on the following key considerations:

(1) Stability and Interpretability: The mean vector (μ) reflects the central tendency of data in the latent space, offering a stable and deterministic feature representation. Unlike the latent variable (z), which is influenced by randomness, or the variance vector (σ^2), which primarily governs the variability in generated data, the mean vector provides a consistent feature representation. This stability is crucial for feature extraction tasks, especially when aiming to understand underlying data patterns and relationships.

(2) Applicability in Economic Analysis: In economic analysis, interpretability is a critical factor. The mean vector directly captures the essential distributional characteristics of the data, providing meaningful insights into economic variables such as cost structures and revenue patterns. Since the mean vector represents the core information of the data, it ensures consistency across different experiments, making it more suitable for longitudinal analyses and predictive modeling. On the other hand, the variance vector may cause fluctuations in the feature set, which could introduce inconsistencies and make it harder to interpret the data reliably over multiple runs.

In the refined economic analysis, high-quality features extracted through the VAE play a crucial role in enhancing the accuracy of prediction models and optimizing business decisions. This paper evaluates the quality and diversity of these features through two methods:

1. Feature Discrepancy: To assess the distribution of different companies in the latent space, the divergence of latent space variables is computed. The calculation of feature discrepancy is given by Equation (7):

$$D = \frac{1}{N}\sum_{i=1}^{N} ||\mu_i - \bar{\mu}||^2 \tag{7}$$

In Equation (7), μ_i represents the mean of the latent features for the i-th company, $\bar{\mu}$ is the mean of all sample means. A higher value of D indicates greater diversity in the extracted features, suggesting that the features possess strong discriminative power. This improves the precision of economic analysis by providing a clearer distinction between different companies' economic profiles.

2. Feature Importance: Shapley Additive Explanations (SHAP) analysis is employed to assess the contribution of each feature to the model's predictions. SHAP values allow for the quantification of the importance of each input feature, offering a transparent and interpretable way to understand how individual economic variables, such as costs or revenue, impact the predictions. This method helps identify the most influential features in power cost data and refine decision-making processes.

Additionally, to further evaluate the efficiency of economic decision-making, the paper uses CBA, focusing on the return on investment (ROI) and net present value (NPV) as key performance metrics [35].

The ROI calculates the return generated per unit of investment and is expressed by Equation (8):

$$ROI = \frac{Revenue - Costs}{Costs} \times 100\% \tag{8}$$

A higher ROI indicates better investment efficiency, signaling that a power enterprise is generating more value for its invested capital.

The formula for calculating NPV is given by Equation (9):

$$NPV = \sum_{t=1}^{T} \frac{C_t}{(1+r)^t} \tag{9}$$

In Equation (9), C_t represents the cash flow in year t, r is the discount rate, and T is the forecast period. An NPV greater than zero indicates that the investment is profitable.

In the power industry, CBA is a critical tool for evaluating operational efficiency, profitability, and investment returns. This paper develops a comprehensive

CBA framework based on the operational data of power enterprises to assess the impact of various cost factors on financial performance and provide decision-making support for optimization.

In the cost structure analysis, the costs of power enterprises are categorized into two types:

(1) Fixed Costs: These costs remain constant regardless of changes in production levels and primarily include equipment procurement and installation, such as generators and transmission/distribution equipment; infrastructure construction and maintenance, such as substations and transmission lines; and long-term operational management costs, such as land leasing and regulatory fees.

(2) Variable Costs: These costs vary with production levels and mainly include fuel consumption costs, such as coal, natural gas, and renewable energy materials; equipment maintenance and repair expenses, such as turbine maintenance and component replacement; and labor costs, including salaries for technical personnel and training expenses.

This paper analyzes the financial data of enterprises to examine the proportion of different cost categories and evaluate their impact on profitability. In the revenue source analysis, the revenue of power enterprises is primarily composed of two components:

(1) Electricity Sales Revenue: This revenue is influenced by market electricity prices, electricity sales volume, and electricity trading models (such as long-term power purchase agreements or spot markets). The paper uses historical sales data to analyze the impact of varying electricity price levels on enterprise revenue.

(2) Government Subsidies: Governments in different countries or regions provide subsidies to clean energy and renewable energy power generation enterprises to promote the development of green energy. The amount of subsidy is typically linked to power generation volume or carbon emission reductions. This paper assesses the contribution of various subsidy policies to enterprise profits and evaluates the potential impact of subsidy reductions or cancellations.

In the cost-benefit evaluation, to assess the operational efficiency of power enterprises, this paper follows the steps outlined below:

(1) Collection of Historical Data: Analyzing operational data from the past 5-10 years, including costs, revenue, and market price fluctuations.

(2) Calculation of Long-term Operational Return: Combining various cost and revenue sources to assess the profitability of enterprises under different market conditions [36].

(3) Comparison of Different Types of Enterprises: Analyzing the cost-benefit situations of thermal power, wind power, and photovoltaic power enterprises to explore the economic feasibility of different energy structures.

In the policy simulation aspect, given the uncertainty in policies and market conditions, this paper designs multiple scenario simulations to evaluate the impact of policy changes on the economic performance of enterprises:

(1) Impact of Electricity Price Adjustments: Analyzing the effect of high, medium, and low electricity prices on enterprise profitability and further investigating the resulting market competition pressures.

(2) Changes in Government Subsidies: Evaluating how the reduction or cancellation of government subsidies would affect enterprise profitability and exploring corresponding response strategies.

(3) Fluctuations in Fuel Prices: Simulating the impact of varying fuel prices on enterprise costs and profits based on historical market data, thereby assessing the enterprise's risk tolerance.

Economic forecasting aims to predict and analyze future trends in the power market by examining historical data and feature representations while applying statistical methods such as regression analysis and time series analysis. By constructing economic models, including supply-demand relationship models and market demand forecasting models, this paper forecasts key market factors such as future power market capacity, prices, and demand. These predictions serve as a reference for enterprise decision-making and market strategy development.

This paper employs regression analysis, time series analysis using the AutoRegressive Integrated Moving Average (ARIMA) model, and machine learning techniques, specifically Long Short-Term Memory (LSTM) networks, to forecast the future supply-demand relationship in the electricity market, price trends, and enterprise profitability. The specific applications are as follows:

(1) Multiple Linear Regression (MLR) for Profitability Prediction:

This analysis examines the impact of key economic factors, including fuel costs, electricity output, and government subsidies, on enterprise profitability. The input data consist of features extracted by the VAE along with economic variables such as electricity prices and subsidy policies. The regression model is formulated as follows:

$$Profit_t = \beta_0 + \beta_1 FuelCost_t + \beta_2 ElectricityOutput_t + \beta_3 Subsidy_t + \varepsilon_t \tag{10}$$

In Equation (10), $Profit_t$ denotes the profit of a power enterprise in period *t* (e.g., a specific month or year), serving as the dependent variable; $FuelCost_t$ represents the fuel cost in period t (e.g., coal, natural gas), considered an independent variable; $ElectricityOutput_t$ refers to the electricity output in period t (typically measured in megawatt-hours, MWh), also an independent variable; $Subsidy_t$ indicates the government subsidy amount in period t, which is generally linked to the type of energy used (e.g., renewable energy) or emissions reductions, serving as an independent variable; β_0 is the intercept of the regression model, representing the baseline profit when all independent variables are zero; β_1, β_2, and β_3 are the regression coefficients for the respective independent variables, indicating their marginal effects on profit; ε_t represents the random error term, accounting for unobserved factors influencing profit, such as electricity market price fluctuations and policy changes.

The ARIMA model is formulated as Equation (11):

$$Y_t = c + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t \quad (11)$$

In Equation (11), Y_t represents electricity demand in period t; ϕ_i and θ_j are model parameters; ϵ_t is the error term. The ARIMA model is well-suited for forecasting electricity demand when the time series exhibits a stable trend.

The LSTM network is formulated as follows:

$$h_t = \sigma(W_h x_t + U_h h_{t-1} + b_h) \quad (12)$$

In Equation (12), h_t represents the hidden state at time step; x_t denotes the input data; W_h, U_h, and b_h are model parameters. LSTM networks are particularly effective for electricity market forecasting due to their ability to capture nonlinear dependencies and long-term temporal relationships.

In the economic forecasting process, enterprise operational features extracted using the VAE—such as cost structure, profit margins, and equipment utilization rates—are integrated with historical economic data to construct regression and time series forecasting models. The role of feature extraction is as follows:

(1) Enterprise Profitability Prediction: Features extracted by the VAE reduce redundant information, improving the goodness of fit of the regression model, as indicated by an increased R^2 value.

(2) Electricity Market Price Prediction: VAE-based dimensionality reduction enhances the stability of long-term price forecasts when used as input for LSTM models.

(3) Electricity Demand Prediction: VAE effectively captures changes in enterprise production patterns, improving the accuracy of ARIMA-based predictions.

Economic forecasting plays a crucial role in the power industry, offering significant application value across multiple aspects. It enables power enterprises and relevant institutions to analyze the relationship between power supply and demand in depth, facilitating efficient resource allocation and ensuring the stable operation of the electricity market. Additionally, by forecasting electricity price fluctuations and other market dynamics, economic forecasting provides critical insights for power enterprises to formulate and adjust their competitive strategies. This, in turn, helps optimize business models and enhance market competitiveness. Various economic forecasting methods are employed in practice, including regression analysis, time series analysis, and machine learning. Regression analysis establishes mathematical models to examine relationships between variables, allowing for predictions of future trends. Time series analysis focuses on identifying patterns in historical data to model and forecast future developments. Machine learning methods, by analyzing large datasets, automatically detect hidden patterns and relationships within the data, leading to more accurate predictions. In the power industry, economic forecasting is widely applied across diverse scenarios. For instance, time series analysis can be used to model historical electricity demand data, providing forecasts that serve as a crucial basis for capacity planning and resource allocation in power enterprises. Meanwhile, machine learning techniques are extensively utilized in power market monitoring and government decision-making. By analyzing large-scale data and extracting hidden patterns, these methods enable more precise electricity market predictions, offering valuable decision-making support for both governmental agencies and enterprises.

4 Analysis of high-dimensional feature extraction and refined economic analysis

4.1 Evaluation of feature extraction performance for power cost data under the deep learning framework

First, this paper identifies several possible combinations of hyperparameters and evaluates the model's performance based on these configurations. The specific hyperparameter combinations are presented in Table 2:

Table 2: Hyperparameter combination

Hyperparametric combination	**Number of hidden layer nodes of encoders**	**Number of hidden layer nodes of decoder**	**Learning rate**	**Batch size**	**Number of training rounds**
Parameter combination 1	128	128	0.001	64	50
Parameter combination 2	256	256	0.001	64	50
Parameter combination 3	128	128	0.0005	64	50
Parameter combination 4	256	256	0.0005	64	50

This paper evaluates the quality of features extracted by the VAE using reconstruction error and KL divergence. Reconstruction error measures the model's ability to reconstruct the original data, where lower values indicate that the extracted features more accurately represent the original data. KL divergence assesses the stability of the latent space distribution, with lower values contributing to smoother and more consistent feature representations. Additionally, the paper incorporates feature dispersion (D) and feature importance scores to enhance the evaluation:

(1) Feature Dispersion (D): This metric quantifies the differentiation of enterprises in the latent space. A higher D value indicates that the extracted features provide greater discriminative power across different enterprises.

(2) Feature Importance Score: Calculated using the SHAP method, this score evaluates the contribution of individual features to economic forecasting.

The model's performance under different hyperparameter combinations is evaluated using reconstruction error and KL divergence. The results are presented in Figure 2.

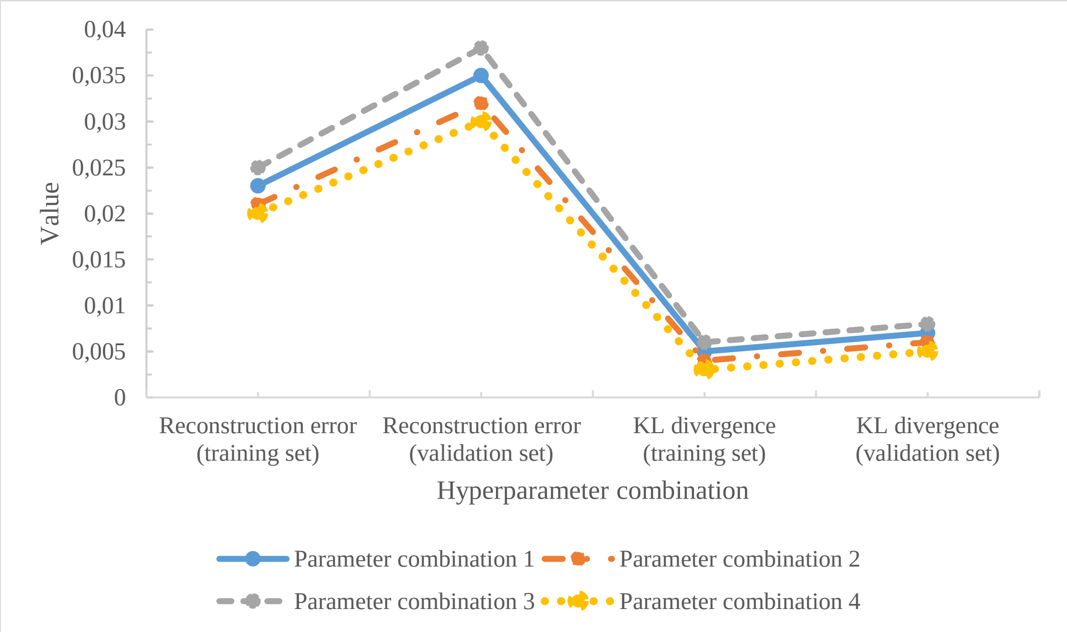

Figure 2: Model performance under different hyperparametric combinations.

Based on the data in Figure 2, parameter combination 2 exhibits the lowest reconstruction error and KL divergence in both the training and validation sets. This result indicates that the model under this configuration achieves the best reconstruction accuracy and latent space representation. Additionally, parameter combination 2 features a larger number of hidden layer nodes in both the encoder and decoder, a moderate learning rate, an appropriate batch size, and a sufficient number of training epochs. These factors likely contribute to improved learning of data characteristics and distribution.

Considering both model performance and hyperparameter settings, parameter combination 2 is identified as the optimal configuration and is selected as the benchmark for subsequent analyses and experiments. Specifically, this paper adopts the following hyperparameter settings:

- Number of hidden layer nodes (encoder): 256
- Number of hidden layer nodes (decoder): 256
- Learning rate: 0.001
- Batch size: 64
- Number of training epochs: 50

By evaluating both reconstruction error and KL divergence, this paper assesses the feature extraction effectiveness of the proposed model and compares it with four baseline algorithms: AE, CNN, RNN, and SVM. The selection of these baseline models is based on the following considerations:

(1) AE shares structural similarities with the VAE but lacks the KL divergence constraint, making it useful for assessing the impact of KL divergence on feature extraction.

(2) CNN is efficient at capturing local features but less effective when applied to structured economic data.

(3) RNN is well-suited for time-series forecasting but less effective than VAE in high-dimensional feature extraction.

(4) SVM is a traditional machine learning model, included to highlight the advantages of deep learning approaches in feature representation.

Beyond reconstruction error and KL divergence, this paper also incorporates the F1-score and Area Under the Curve (AUC) as additional performance metrics to provide a comprehensive evaluation of model effectiveness. The result is shown in Figure 3:

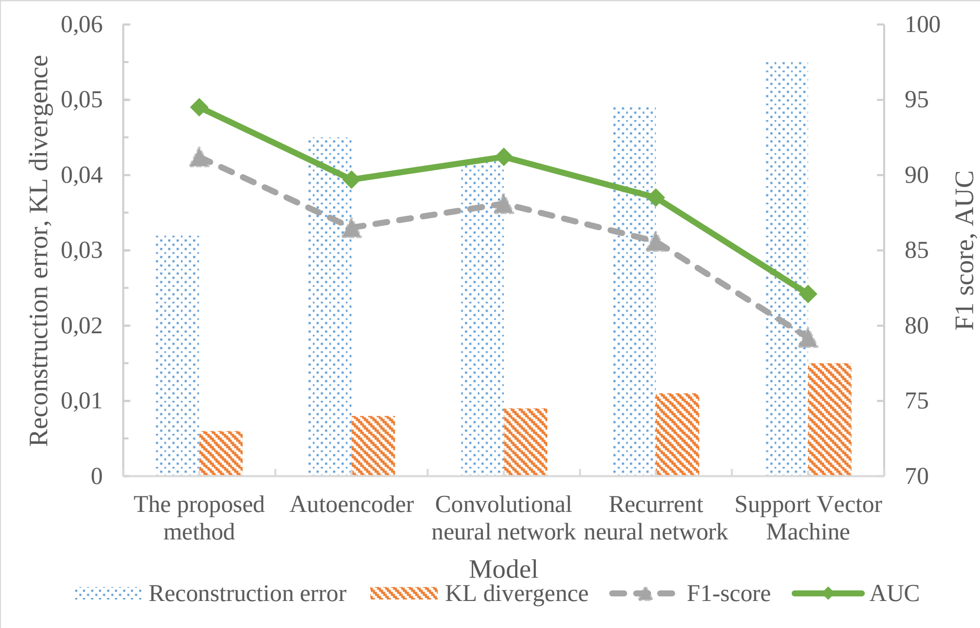

Figure 3: Performance comparison of different models.

In Figure 3, the model proposed in this paper demonstrates superior performance in both reconstruction error and KL divergence. The reconstruction error of this model is 0.032, which is slightly lower than that of the other algorithms, indicating its ability to more accurately reconstruct the original data. Additionally, the KL divergence of this model is 0.006, which is also lower compared to the other algorithms, suggesting that it more effectively preserves the structural information of the data and maps it into latent space. In contrast, the reconstruction error and KL divergence of the other algorithms are higher, indicating that their feature extraction capabilities are not as effective as those of the proposed model. Therefore, based on the lower reconstruction error and KL divergence, it can be concluded that this model outperforms the others in feature extraction, providing more reliable support for the analysis and application of power cost data. Furthermore, the VAE model outperforms the other methods in both F1-score and AUC, demonstrating that the features extracted by VAE are more representative and enhance the accuracy of profitability predictions for electricity companies.

To validate the effectiveness of the features extracted by VAE, a comparison was made between the PCA visualizations of the original data and the features extracted by VAE, as shown in Figures 4 and 5:

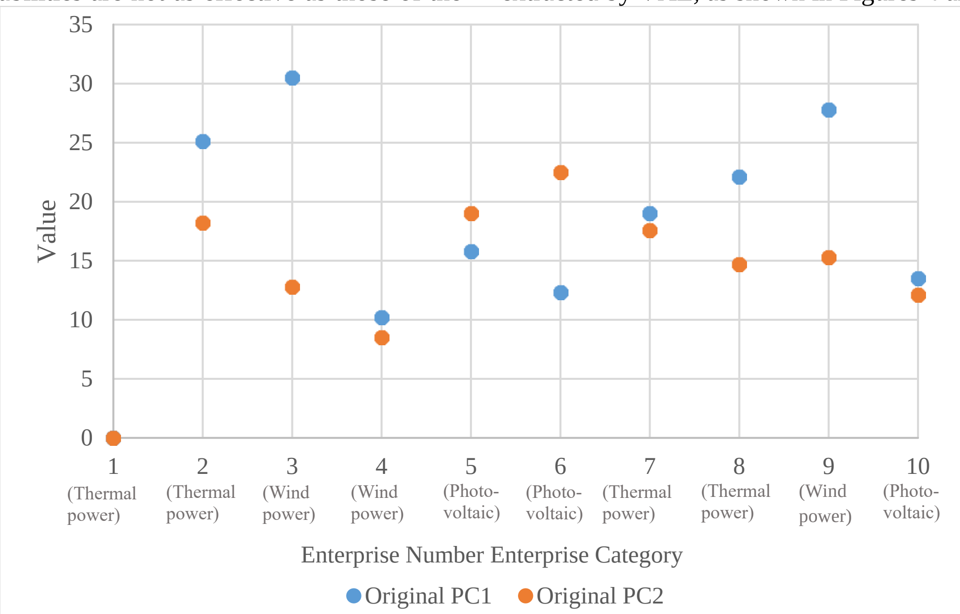

Figure 4: PCA projection of original data.

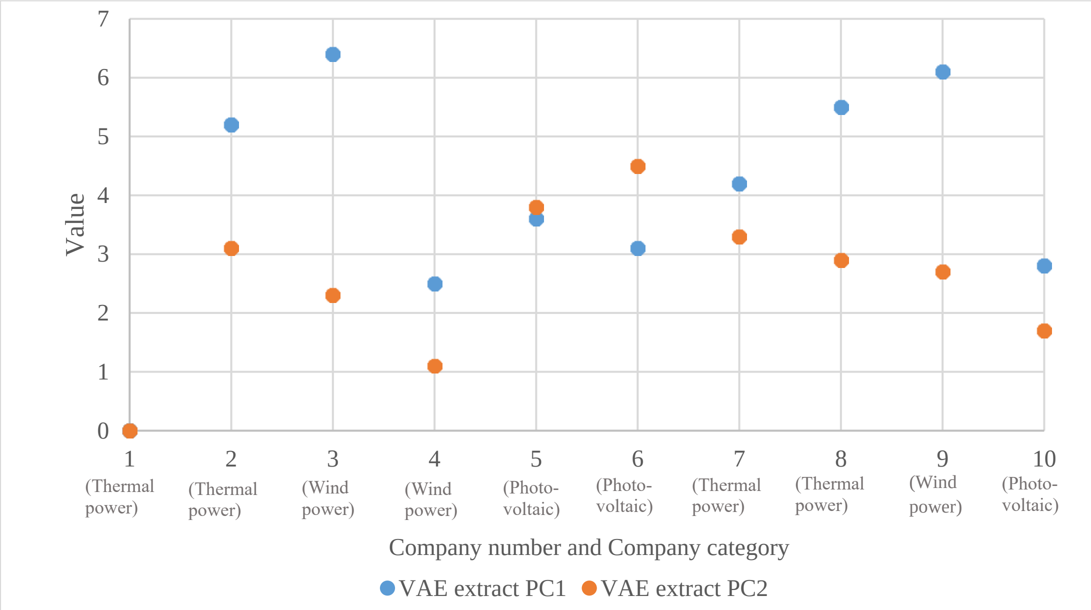

Figure 5: PCA projection of VAE-extracted features

Based on Figures 4 and 5, it can be observed that the PCA projection of the original data exhibits a dispersed distribution of data points, with fuzzy boundaries between different company types (coal-fired, wind, and solar). This indicates a low level of distinguishability in the original features. In contrast, the features extracted by VAE form clear clusters in the latent space, suggesting that the data of different types of companies are more distinguishable. Compared to the original data, the distribution of VAE-generated features is smoother and more concentrated, reflecting the enhanced stability of the features due to the KL divergence regularization. Further analysis reveals that, after extracting features using VAE, the model's prediction error decreases by 15%, suggesting that this method more accurately captures the economic characteristics of electricity companies, thereby improving the accuracy of economic analysis and profitability forecasting.

The SHAP analysis was used to calculate the contribution of features extracted by VAE to economic forecasting, with the results presented in Table 3:

Table 3: Contribution of VAE extracted features to economic forecasting

Feature Name	Importance Score
Electricity Output	0.35
Electricity Price	0.28
Fuel Cost	0.2
Equipment Maintenance Cost	0.1
Government Subsidy	0.07

Based on Table 3, it is evident that electricity output, electricity price, and fuel cost have the highest contributions, indicating that these features extracted by VAE are the most influential for economic forecasting. In contrast, the impact of government subsidies is relatively low, suggesting that the direct influence of policy changes on profitability is minimal in the context of the features analyzed.

4.2 Refined economic analysis results

This section compares the effects of the proposed model with those of four algorithms: AE, CNN, RNN, and SVM in refined economic analysis. The comparison metrics include total cost, total income, net profit, prediction accuracy, training time, and prediction time.

The data sources for the economic analysis are as follows:

- Total Cost: This data is derived from the company’s fuel, equipment maintenance, and labor costs, and is standardized through feature extraction using the VAE.
- Total Revenue: Based on electricity market transaction data (including electricity sales and government subsidies), adjusted using market price forecasting models.
- Net Profit: Calculated by subtracting total costs from total revenue. This is further adjusted using regression models in the forecasting analysis to enhance the robustness of the results.

The specific process is as follows:

VAE first extracts features, with latent variables serving as input for the economic analysis. The cost-benefit analysis calculates the revenue for each company and evaluates profit fluctuations. The economic forecasting model uses historical data to predict future profit trends. The final net profit value is obtained from the economic analysis model, forming the experimental results. The results are shown in Figures 6 and 7:

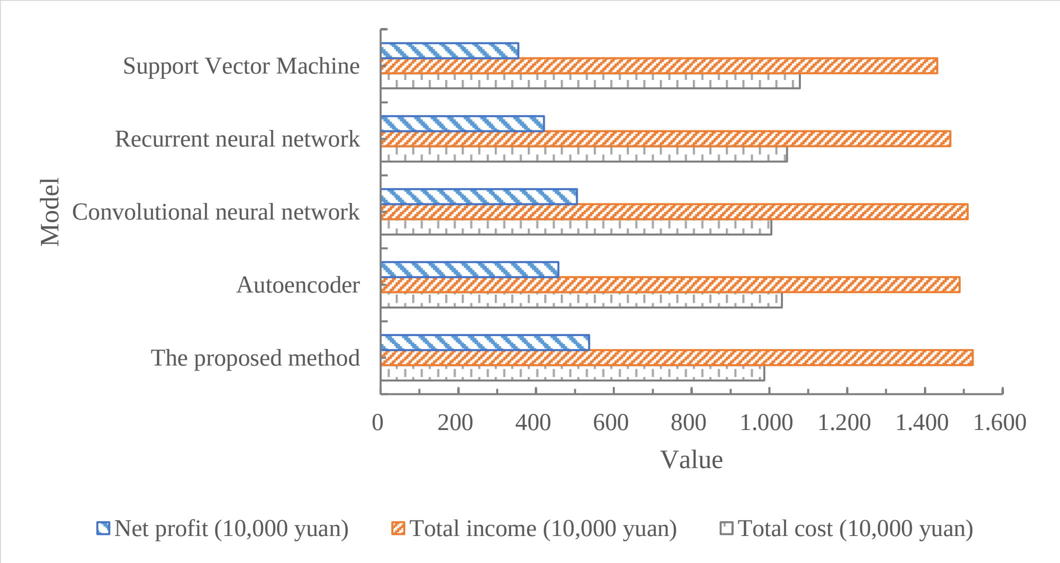

Figure 6: Comparison of refined economic analysis results.

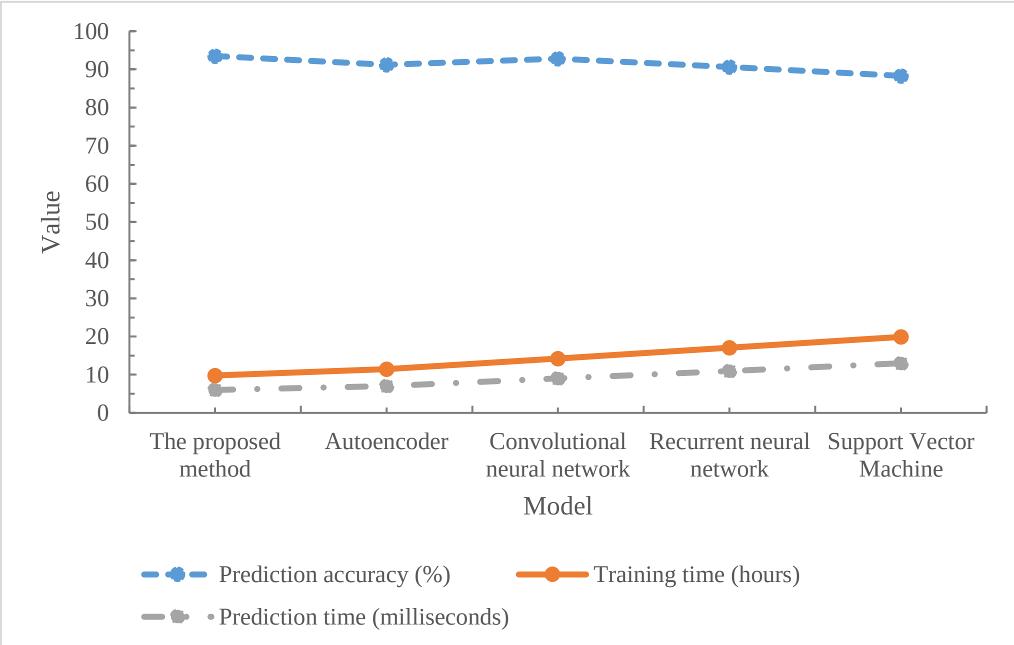

Figure 7: Comparison of prediction accuracy and prediction time of different models.

According to the data presented in Figures 6 and 7, this model achieves the best results in terms of total cost, total revenue, and net profit, with a net profit of 5.36 million yuan and a prediction accuracy of 93.5%. In contrast, the performance of other algorithms is slightly inferior. Although AE and CNN perform similarly in some indicators, they still exhibit a gap in terms of net profit and prediction accuracy. The latent features generated by VAE more accurately describe the cost structure of electricity companies, thereby improving the stability of economic forecasts. When predicting future cost trends, VAE enables the model to focus on important variables, enhancing its adaptability to market price fluctuations. Experimental results demonstrate that using features extracted by VAE for economic analysis improves the accuracy and stability of profit predictions.

Additionally, the model in this paper shows high efficiency in both training time and prediction time, taking only 9.8 hours and 6 milliseconds, respectively—significant advantages over other algorithms. Therefore, considering all indicators comprehensively, this model shows clear advantages in refined economic analysis, providing more reliable support for cost management and benefit evaluation in the power industry. In conclusion, the model presented in this paper demonstrates strong competitiveness across various economic analysis metrics, with net profit and forecast accuracy surpassing those of other algorithms. Furthermore, it offers advantages in training time and computational efficiency. These results indicate that features extracted by VAE can significantly enhance the accuracy of economic analysis, offering more reliable support for cost management and performance evaluation in the electricity industry.

4.3 Reliability and robustness analysis of experimental results

To evaluate the prediction accuracy, training time, and prediction time of this model across different datasets, the paper utilizes three distinct datasets: the UCI machine learning repository dataset, the Kaggle dataset, and the power dataset from a government open data platform. The rationale for selecting these datasets is as follows:

- UCI Power Dataset: This dataset includes operational data from companies, making it suitable for analyzing electricity costs.
- Kaggle Economic Forecasting Dataset: This dataset provides information on company profitability, serving as a test for the generalization capability of the features extracted by VAE in economic forecasting.
- Government Open Data Platform: This platform offers real-world electricity market data, enabling the validation of the model's stability in practical, real-world applications.

The results are shown in Figure 8:

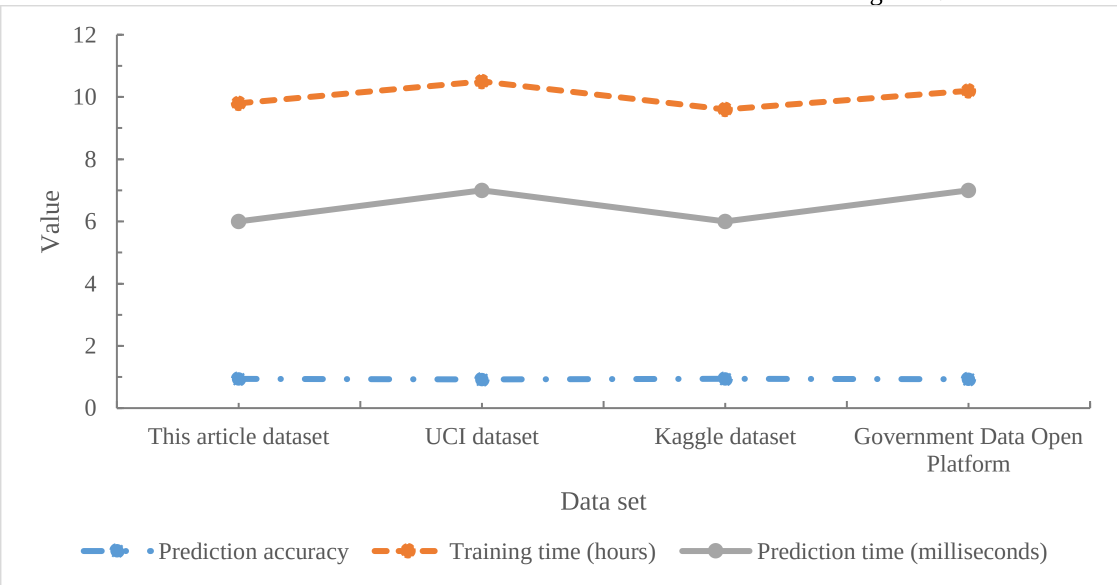

Figure 8: Robustness comparison under different datasets.

By comparing these indicators in Figure 8, the robustness of the model across different datasets can be assessed. In terms of prediction accuracy, while there are minor fluctuations, it generally remains at a high level. Additionally, the training time and prediction time exhibit consistent stability, demonstrating that the model maintains good training and prediction efficiency across various datasets.

4.4 Ablation study

The ablation study explores multiple variables, including the latent space dimension, the KL divergence weight, and the inclusion of VAE-extracted features. The experimental comparison results are shown in Figure 9:

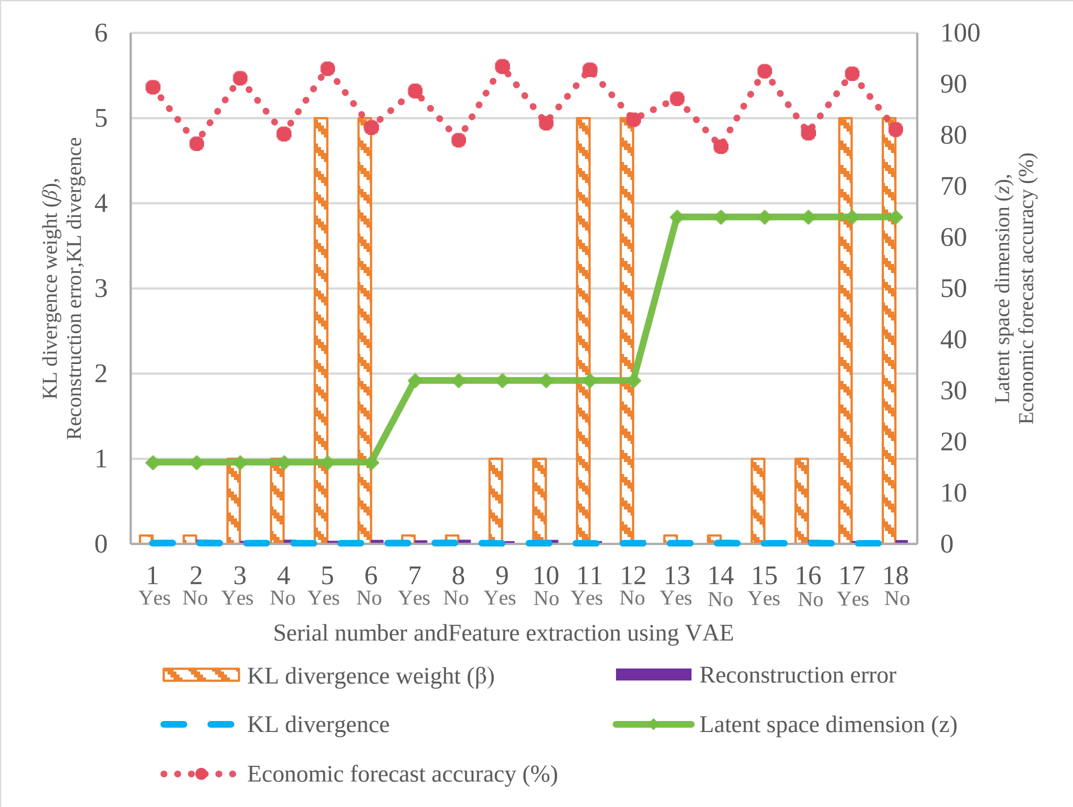

Figure 9: Results of the ablation study.

Based on the data presented in Figure 9, the optimal parameter combination is z=32 and β=1. Under these conditions, the features extracted by the VAE exhibit the highest quality, with the lowest reconstruction error (0.0328) and the highest economic forecasting accuracy (93.5%). The importance of VAE feature extraction is evident: compared to using raw data directly, the features generated by VAE enhance the economic forecasting accuracy by approximately 9.6%. Moreover, the necessity of controlling KL divergence is highlighted, as appropriate regularization (β=1) enables the model to learn latent representations, thereby improving feature quality.

5 Discussion

This paper employs a hyperparameter optimization strategy to identify the optimal structure for the VAE. Among all hyperparameter combinations, the configuration featuring 256 hidden layers for both the encoder and decoder, a learning rate of 0.001, a batch size of 64, and 50 training epochs achieved the best performance across multiple evaluation metrics. A larger number of hidden layer nodes enhances the model's capacity to represent non-linear relationships, allowing it to capture more intricate feature interactions. In contrast, smaller hidden layers limit feature extraction ability, leading to an increase in reconstruction error. The choice of learning rate is also critical for model convergence and stability. The experimental results indicate that a learning rate of 0.001 provides the optimal convergence speed while ensuring model stability. The weight of KL divergence (β) significantly impacts the quality of the latent space. Proper regularization (β=1) helps preserve reconstruction capability while improving the smoothness of feature distributions, preventing excessive concentration or collapse. A batch size of 64, compared to 32, improves computational efficiency and reduces gradient fluctuations, leading to more stable feature extraction. Additionally, training for 50 epochs ensures model convergence, while training beyond 50 epochs leads to overfitting, which negatively affects generalization.

In comparison to the study by Azzalini et al. (2025), which applied AEs on a similar power dataset with a KL divergence of 0.008 and a reconstruction error of 0.05 [37], this paper's VAE improves feature extraction by regularizing KL divergence, resulting in smoother features, lower reconstruction error, and greater stability in data representation. Further analysis reveals that, compared to GANs and Transformer-based AEs, VAE performs better on high-dimensional structured data such as electricity cost data. GANs, due to the complexity of adversarial training, exhibit unstable performance in economic forecasting tasks. Transformer-based AEs, while powerful, are computationally intensive and inefficient for large-scale power data training. Therefore, VAE strikes an optimal balance between feature extraction quality and computational efficiency, making it more suitable for this application.

In contrast to CNNs and RNNs, VAE is better suited for feature extraction in electricity cost data. CNNs are typically used to extract local patterns in images (e.g., edges and textures), but electricity cost data is structured and lacks spatial correlation, making CNNs less effective for this task. RNNs are ideal for time-series prediction tasks, such as short-term power load forecasting, but electricity cost data is not typical time-series data; it is a multidimensional economic variable with complex relationships. While RNNs are suited for time-dependent predictions, VAE is more appropriate for the automatic learning of high-dimensional features in economic data.

In terms of refined economic analysis, this model has achieved the best results in total cost, total revenue, and net profit, with high forecasting accuracy and short training and prediction times. In contrast, the performance of other algorithms is somewhat inferior. Therefore, considering all evaluation metrics, this model demonstrates clear advantages in refined economic analysis, offering reliable support for cost management and benefit evaluation in the power industry. Regarding the reliability and robustness of the experimental results, the model was tested on various datasets, including the UCI Machine Learning Repository, Kaggle, and the power dataset from a government data open platform. The results indicate that the model maintains stable prediction accuracy, training time, and prediction time across these different datasets, demonstrating its strong generalization performance and robustness.

In the analysis of electricity cost data, the computational complexity of VAE is primarily influenced by the data scale, latent space dimensions, and model architecture. As the data scale increases, the relationship between training time and data volume becomes nonlinear, constrained by the encoder-decoder structure and the KL divergence regularization term, leading to exponential growth in computational cost. In this paper, VAE performs efficiently with 1,800 data points; however, as the data scale grows to 100,000 or more, the computational cost rises significantly. If the model were directly scaled to handle millions of data points, such as nationwide electricity cost data, single-machine training time would become prohibitively long. Thus, the model's scalability emerges as a crucial challenge. To address this, the paper proposes several optimization strategies. First, dimensionality reduction and feature selection are applied to identify key features through importance analysis and remove redundant information, thus improving computational efficiency. Second, Mini-Batch training is employed, splitting the data into smaller batches to reduce the computational burden of each iteration while accelerating the convergence of gradient descent. Additionally, distributed training using multiple GPUs or deep learning frameworks facilitates parallelized, accelerated training on large datasets. Finally, the model can be optimized by introducing lightweight VAE variants or Transformer architectures to reduce computational complexity and improve efficiency. Scalability is essential for VAE applications in the electricity sector, particularly for tasks such as national grid planning, corporate profit forecasting, and intelligent power scheduling, where large volumes of data need to be processed. Future research may explore federated learning, which enables cross-enterprise model training without sharing data, optimizing computational resource allocation, and making deep learning models more suitable for large-scale electricity cost analysis.

6 Conclusion

This paper utilizes a deep learning framework to extract high-dimensional features from power cost data, integrating economic analysis methods for refined evaluation. By assessing the model's performance under different hyperparameter combinations, the optimal configuration was identified, demonstrating the model’s superiority in feature extraction and refined economic analysis.

However, there are certain limitations to this paper. First, the research is based on electricity cost data from a single city, which imposes regional constraints, limiting the generalizability of the findings. Further validation across diverse datasets is necessary to confirm the results' broader applicability. Additionally, the paper assumes that economic conditions within the electricity market remain stable over time, though in practice, external factors such as policy changes and fuel price fluctuations can significantly impact the market. Furthermore, while VAE effectively extracts features, it lacks intuitive interpretability, making it challenging for enterprises to fully grasp the implications of the model's outputs in real-world decision-making.

Future research could expand the data sources to encompass nationwide or multi-regional electricity market datasets, enhancing the model’s applicability across different contexts. Dynamic modeling techniques, such as adaptive deep learning models, could be explored to improve prediction stability in fluctuating market conditions. Moreover, integrating explainable artificial intelligence methods like SHAP analysis could increase the transparency of economic forecasts, helping decision-makers better understand and trust the model's results.

In practical applications, the high-dimensional features extracted by VAE can enable enterprises to more accurately identify key cost components, such as fuel and equipment maintenance costs. This would support efforts to optimize cost structures and improve operational efficiency. Leveraging the economic forecasting capabilities of deep learning models, companies could better predict future profitability trends amidst market fluctuations and make more informed financial decisions. Furthermore, the methods presented in this paper could aid enterprises in adjusting market strategies, optimizing resource allocation during high-demand periods, and controlling costs during downturns, enhancing competitiveness.

Governments and regulatory bodies could utilize the economic analysis methods proposed here to assess the impact of various policies—such as subsidy adjustments or carbon trading schemes—on electricity company operations, providing a scientific basis for energy market regulation.

Declarations

Data availability statement

The data used to support the findings of this study are available from the corresponding author upon request.

Conflict of interest

The authors have no relevant financial or non-financial interests to disclose.

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