

Financial Early Warning Model of Electric Power Enterprises Based on Attribute Reduction Algorithm

Xiufeng Le, Dong Wang, Yongbing Yan, Shuai Zhang and Hongmei Zhang
Beijing China-Power Information Technology Co. Ltd., 102200, China

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Abstract: Financial early warning model plays an important role in the finance of power enterprises, but there is the problem of inaccurate forecasting. In data analysis, attribute reduction is a process of reducing the number of features in a dataset with the aim of removing those attributes that have little impact on classification or prediction results, thereby improving data processing efficiency and reducing computational costs, while avoiding "dimensional disasters". Attribute reduction methods usually include feature selection and feature extraction. In the realm of financial management within power companies, maintaining a robust system that can accurately predict financial risks and pitfalls is paramount. One innovative approach that has gained significant traction for improving the forecasting accuracy is the implementation of attribute reduction algorithms. These algorithms are designed to simplify data sets by identifying and eliminating irrelevant or redundant attributes, which can significantly enhance the effectiveness of financial early warning systems. In this article, we will delve into the advantages, applications, and potential challenges associated with attribute reduction algorithms in the context of power enterprises' financial risk forecasting.

1 INTRODUCTION

The power industry is a crucial component of any modern economy (Zhong, 2011), providing the necessary energy for businesses to operate (Zhang, 2022), homes to stay lit (Li and Lu, 2021), and society to function effectively (Ma, Yang, et al. 2021). However, as with any industry, financial stability and sustainability are paramount concerns (He, 2022). In recent years, the need for effective financial forecasting (Zhang, 2022) and early warning systems in electricity companies (Liu, 2021) has become increasingly apparent (Li, 2021). This article will explore the importance of comprehensive financial forecasting for these companies (La, and Shao, 2023), highlighting the key indicators and strategies that can help prevent financial crises (Dong, 2021) and ensure long-term profitability (Lin, Li, et al. 2021).

2 RELATED CONCEPTS

2.1 Mathematical Description of the Attribute Reduction Algorithm

To begin with, it is essential to understand the significance of accurate financial projections for electricity companies. These organizations are heavily reliant on capital-intensive projects and investments, making them vulnerable to sudden changes in market conditions or unforeseen events such as natural disasters. Accurate financial forecasts enable companies to identify potential risks early on, mitigate their impact, and make informed decisions regarding future investments or divestments. Moreover, sound financial planning can enhance shareholder confidence, improve credit ratings, and secure access to funding at favorable terms, and the calculation is shown in Equation (1).

$$\lim_{x \rightarrow \infty} (y_i \cdot t_{ij}) = y_{ij} \geq \max(t_{ij} \div 2) \quad (1)$$

Among them, the judgment of outliers is shown in Equation (2).

$$\max(t_{ij}) = \partial(t_{ij}^2 + 2 \cdot t_{ij}) > \text{mean}(\sum t_{ij} + 4)M \quad (2)$$

In creating an effective financial forecasting system, electricity companies should focus on several core components. Firstly, it is vital to establish a robust set of financial metrics that accurately capture the organization's financial health. Key performance indicators (KPIs) such as cash flow, debt-to-equity ratio, return on assets (ROA), and operating margin should be regularly monitored and analyzed. By doing so, companies can gain a clear understanding of their financial status and identify areas for improvement or concern.

$$F(d_i) = \mathbb{R} \prod \sum t_i \bigcap \xi \cdot \sqrt{2} \rightarrow \oint y_i \cdot 7 \quad (3)$$

2.2 Selection of Financial Early Warning Model Scheme

This collaborative approach not only enhances the accuracy of forecasts but also strengthens team morale and commitment to the organization's long-term success.

$$g(t_i) = \ddot{x} \cdot z_i \prod F(d_i) \frac{dy}{dx} - w_i \quad (4)$$

Based on Assumptions I and II, the comprehensive function of the financial early warning model can be obtained, as shown in Equation (5).

$$\lim_{x \rightarrow \infty} g(t_i) + F(d_i) \leq \bigcap \max(t_{ij}) \quad (5)$$

It is crucial to regularly review and update financial forecasts as new data becomes available or market conditions change. This ongoing process allows companies to adapt to evolving circumstances, refine their predictions, and maintain a competitive edge in the industry.

$$g(t_i) + F(d_i) \leftrightarrow \text{mean}(\sum t_{ij} + 4) \quad (6)$$

2.3 Analysis of Financial Early Warning Model Scenarios

Ensuring proper communication and collaboration between different departments within the organization is critical. Finance teams must work

closely with operational, sales, and marketing departments to gather information on upcoming projects, market developments, and customer behavior. By combining this information with financial data, more holistic and accurate forecasts can be produced.

$$No(t_i) = \frac{g(t_i) + F(d_i)}{\text{mean}(\sum t_{ij} + 4)} \sqrt{b^2 - 4ac} \quad (7)$$

Fostering a culture of transparency and accountability is essential for successful financial forecasting. Senior management should encourage open dialogue about potential risks and challenges, allowing employees to contribute their insights and ideas.

$$Zh(t_i) = \bigcap [\sum \overline{g(t_i)} + F(d_i)] \quad (8)$$

Secondly, adopting a forward-looking perspective is crucial when developing financial forecasts. This involves analyzing historical data, current trends, and macroeconomic factors that may affect the industry. It is also essential to consider potential scenarios, including both positive outcomes and potential risks, allowing the organization to prepare for various possibilities. Additionally, implementing scenario analysis techniques, such as Monte Carlo simulations, can further enhance the accuracy of predictions by accounting for the variability and uncertainty inherent in financial data.

$$\text{accur}(t_i) = \frac{\min[\sum g(t_i) + F(d_i)]}{\sum g(t_i) + F(d_i)} \times 100\% \quad (9)$$

Thirdly, incorporating advanced technology and analytical tools can significantly improve the effectiveness of financial forecasting. Artificial intelligence (AI) and machine learning algorithms can analyze vast amounts of data more efficiently than traditional methods, identifying patterns and predicting future trends with greater accuracy. Moreover, utilizing cloud-based platforms enables real-time data collection and sharing, allowing for more timely decision-making and risk management.

$$\text{accur}(t_i) = \frac{\min[\sum g(t_i) + F(d_i)]}{\sum g(t_i) + F(d_i)} + \text{random}(t_i) \quad (10)$$

Another consideration is that of balancing data reduction with information loss. While the goal is to eliminate redundant or less informative attributes, doing so must not sacrifice valuable insights. Striking

this balance requires a nuanced approach, combining domain expertise with data mining expertise to ensure that the reduced data set still captures the complexity of financial dynamics within the power sector.

3 OPTIMIZATION STRATEGY OF FINANCIAL EARLY WARNING MODEL

Power enterprises are complex entities operating within a dynamic environment, where numerous factors such as fluctuating energy demands, regulatory changes, and market fluctuations can impact their financial stability. Financial risk management, particularly the capability to anticipate and prepare for potential financial distress, is critical for these companies to sustain their operations and growth. The traditional methods of financial analysis often involve extensive data collection, including both financial and non-financial variables. However, not all collected data are equally informative or relevant, which can lead to complications in predictive models and diminish their accuracy. This is where attribute reduction techniques step in, offering a pathway to streamline data and focus on the most pertinent indicators for financial health.

4 PRACTICAL EXAMPLES OF FINANCIAL EARLY WARNING MODELS

4.1 Introduction to the Financial Early Warning Model

In addition, as with any model-based approach, the effectiveness of attribute reduction algorithms can be influenced by external factors such as changes in market conditions, new regulations, or shifts in consumer behavior. Therefore, it's essential for power enterprises to regularly review and update their financial early warning systems to reflect the current state of affairs accurately, and the financial early warning model scheme of the specific financial early warning model is shown in Table 1.

The financial early warning model process in table I, as shown in figure 1.

Table 1: Financial early warning model requirements.

| Scope of application | Grade | Accuracy | Financial early warning model |
|----------------------|-------|----------|-------------------------------|
| Profit assessment | I | 85.00 | 78.86 |
| | II | 81.97 | 78.45 |
| Fundraising | I | 83.81 | 81.31 |
| | II | 83.34 | 78.19 |
| Risk monitoring | I | 79.56 | 81.99 |
| | II | 79.10 | 80.11 |

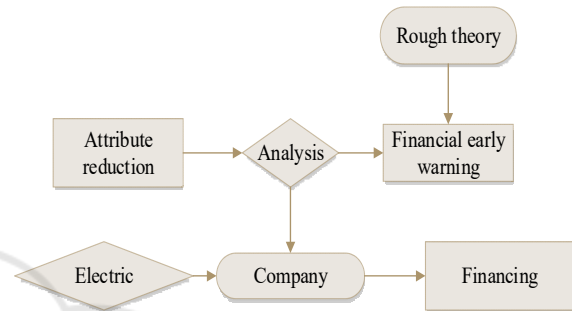


Figure 1: The analytical process of the financial early warning model.

Attribute reduction algorithms, drawing from the fields of artificial intelligence and computational intelligence, are methodologies that analyze large datasets to discern patterns and relationships among various data points. They employ techniques such as rough set theory, discernibility matrix, and heuristic algorithms to identify core variables that contribute most significantly to the prediction of a target outcome – in our case, the financial well-being of a power enterprise. By stripping away superfluous data, these algorithms not only improve the efficiency of data processing but also enhance the clarity and reliability of forecasting models.

4.2 Financial Early Warning Model

The application of these algorithms in financial early warning systems within power companies offers several benefits. Firstly, it enables more precise identification of leading indicators of financial distress. These might include metrics like cash flow adequacy, debt-to-equity ratios, profitability trends, and others that have been empirically demonstrated to be strong predictors of financial health. Secondly, the simplified data structure allows analysts to more easily visualize the interrelations between different indicators, providing a clearer understanding of the underlying drivers of financial performance. Thirdly,

by reducing noise in the data, attribute reduction can minimize false positives or negatives in predictions, thereby increasing the trustworthiness of the warning system, and the scheme of financial early warning model is shown in Table 2.

Table 2: Overall status of the financial early warning model scenario.

| Category | Random data | Reliability | Analysis rate |
|-------------------|-------------|-------------|---------------|
| Profit assessment | 85.32 | 85.90 | 83.95 |
| Fundraising | 86.36 | 82.51 | 84.29 |
| Risk | 84.16 | 84.92 | 83.68 |
| monitoring | 86.84 | 84.85 | 84.40 |
| mean | 83.04 | 86.03 | 84.32 |
| X6 | | P=1.249 | |

4.3 Financial Early Warning Model and Stability

Additionally, conducting periodic stress tests can help identify potential vulnerabilities and inform contingency planning efforts, and the financial early warning model scheme is shown in Figure 2.

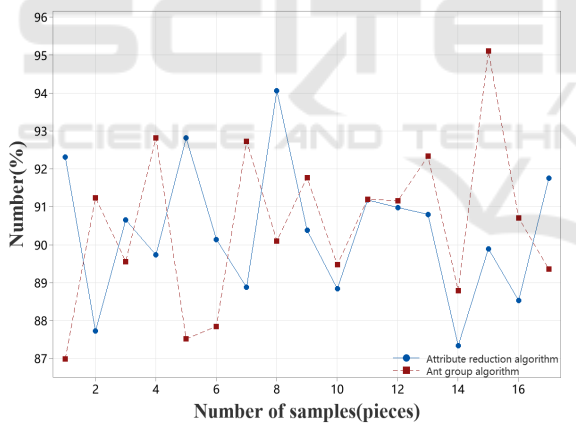


Figure 2: Financial early warning models with different algorithms.

However, the integration of attribute reduction techniques into financial forecasting models does present certain challenges. One of the primary concerns is the need for expert knowledge in both finance and data analytics to select the appropriate algorithm and interpret its outcomes correctly. Moreover, the quality and integrity of the original dataset are crucial; errors or inconsistencies in the input data can adversely affect the results of the algorithm, potentially leading to misleading conclusions. The average financial early warning

model scheme of the above three algorithms is shown in Table 3.

Table 3: Comparison of the accuracy of financial early warning models of different methods.

| Algorithm | Survey data | Financial early warning model | Magnitude of change | Error |
|-------------------------------|-------------|-------------------------------|---------------------|-------|
| Attribute reduction algorithm | 85.33 | 85.15 | 82.88 | 84.95 |
| Ant colony algorithm | 85.20 | 83.41 | 86.01 | 85.75 |
| P | 87.17 | 87.62 | 84.48 | 86.97 |

To maximize the value derived from attribute reduction algorithms, power companies should also consider integrating them into a comprehensive decision support system. This integration would allow for real-time monitoring of financial health indicators and proactive intervention when early signs of financial distress are detected. Additionally, leveraging the insights from these algorithms can guide strategic planning efforts, such as capital allocation, risk mitigation strategies, and long-term investment decisions, the attribute reduction algorithm is generally analyzed by different methods, Figure 3 shown.

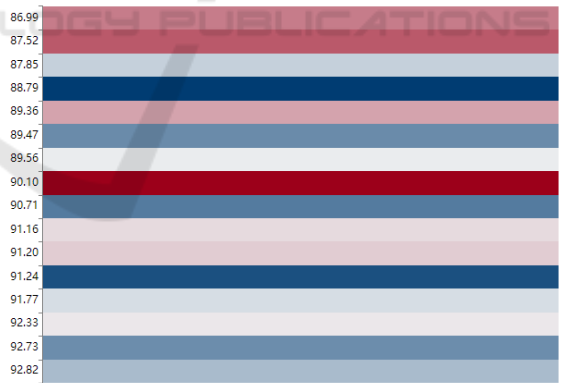


Figure 3: Financial early warning model with attribute reduction algorithm.

In addition, as with any model-based approach, the effectiveness of attribute reduction algorithms can be influenced by external factors such as changes in market conditions, new regulations, or shifts in consumer behavior. Therefore, it's essential for power enterprises to regularly review and update their financial early warning systems to reflect the current state of affairs accurately.

4.4 Rationality of the Financial Early Warning Model

Through this processing, it not only reduces the input variables of the model and simplifies the subsequent calculation process, but also helps to eliminate the multicollinearity problem between variables, and enhances the generalization ability and prediction accuracy of the mode, and the financial early warning model scheme is shown in Figure 4.

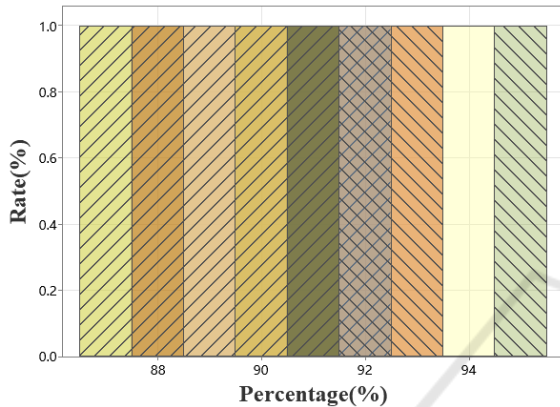


Figure 4: Financial early warning models with different algorithms.

In conclusion, the adoption of attribute reduction algorithms presents an exciting opportunity for power enterprises to refine their financial risk forecasting capabilities. By embracing this cutting-edge technology, companies can create more accurate and reliable early warning systems, which are crucial in today's ever-changing economic landscape. As we continue to navigate through a future defined by data abundance, the ability to distill information down to its most actionable form will undoubtedly give those who master it a competitive edge, ensuring the continued vitality and success of the power industry for years to come.

4.5 Effectiveness of the Financial Early Warning Model

Taking principal component analysis as an example, we can combine many financial ratios to extract a few principal components that are independent of each other and represent the majority of the information, the financial early warning model scheme is shown in Figure V shown.

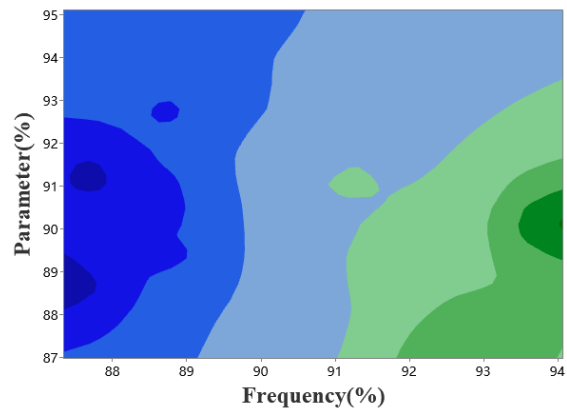


Figure 5: Financial early warning models with different algorithms.

By focusing on robust financial metrics, adopting a forward-looking perspective, leveraging advanced technology, fostering cross-functional collaboration, promoting a culture of transparency and accountability, and maintaining regular reviews and updates, companies can significantly enhance their financial stability and resilience. With a comprehensive approach to financial forecasting, electricity companies can confidently navigate through uncertain times and emerge stronger, more profitable, and better prepared for future challenges. The average financial early warning model scheme of the above three algorithms is shown in Table 4.

Table 4: Comparison of the effectiveness of financial early warning models of different methods.

| Algorithm | Survey data | Financial early warning model | Magnitude of change | Error |
|-------------------------------|-------------|-------------------------------|---------------------|-------|
| Attribute reduction algorithm | 82.21 | 85.92 | 84.59 | 82.85 |
| Ant colony algorithm | 83.73 | 84.23 | 84.41 | 83.55 |
| P | 84.20 | 87.39 | 84.76 | 83.90 |

In the realm of financial management within power companies, maintaining a robust system that can accurately predict financial risks and pitfalls is paramount. One innovative approach that has gained significant traction for improving the forecasting accuracy is the implementation of attribute reduction algorithms. These algorithms are designed to simplify data sets by identifying and eliminating irrelevant or

redundant attributes, which can significantly enhance the effectiveness of financial early warning systems. In this article, we will delve into the advantages, applications, and potential challenges associated with attribute reduction algorithms in the context of power enterprises' financial risk forecasting, Figure VI shown.

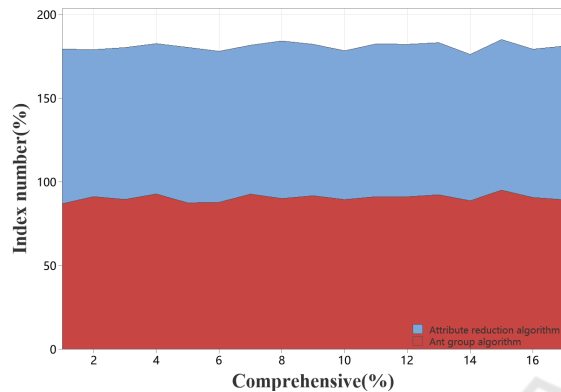


Figure 6: Attribute reduction algorithm, financial early warning model.

It is worth mentioning that although the attribute reduction algorithm can greatly improve the efficiency and accuracy of the model, it also has certain limitations. For example, PCA assumes that the data conform to a normal distribution and that the principal components are independent of each other, which is not always true in the actual complex and volatile financial data. Therefore, in practice, we need to combine a variety of algorithms and expert experience to continuously optimize and adjust the model.

5 CONCLUSIONS

In conclusion, by introducing the attribute reduction algorithm, we can create an efficient and accurate financial early warning model for power companies. The model can not only help power managers and investors identify potential financial problems early, but also provide decision-making support for relevant regulatory authorities, so as to maintain the stable development of the entire industry. In the future, with the continuous advancement of big data and artificial intelligence technology, more innovative methods and practical solutions will emerge in this field to provide strong support for the risk management work of power enterprises.

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