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Backpropagation Artificial Intelligence with Grey System Theory

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ABSTRACT

The paper proposes an early warning system for corporate financial risk using an improved BP (Backpropagation) neural network integrated with grey system theory. The author highlights the critical role of small and medium enterprises (SMEs) in China's economy and their vulnerability to financial distress due to poor financial management, inadequate internal controls, and external market pressures. To address this, a three layer Grey BP neural network model is constructed, featuring 16 financial input indicators, 9 hidden nodes, and 4 output categories representing different risk levels. The model is trained using financial data from 2000–2004 and validated with 2005–2006 data from 93 firms. Experimental results show high prediction accuracy, with an R-value exceeding 0.889, particularly for one year ahead (T-1) forecasts compared to two year ahead (T-2). The study concludes that the Grey BP neural network effectively identifies emerging financial risks, offering enterprise managers a reliable tool for proactive risk mitigation. Its adaptability, self learning capabilities, and minimal data requirements make it especially suitable for dynamic, complex economic environments. The research contributes to the growing body of work applying artificial intelligence to financial early warning systems and demonstrates the practical value of hybrid models that combine grey theory with neural networks for enhanced forecasting precision and generalization.

Keywords: Financial Risk, Early Warning System, Grey BP Neural Network, Small And Medium Enterprises (SMEs), Artificial Neural Networks, Risk Prediction

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1. Introduction

As the market economy continues to evolve, businesses in our nation are experiencing swift growth. They have emerged not only as the most dynamic economic agents in the market economy but also as its source of vitality. Their sheer volume underscores the significance of enterprises. By 2003, there were more than 600,000 businesses registered with our country's industrial and commercial regulatory bodies, alongside 27.9 million individual enterprises. They serve as a crucial engine for economic expansion. The contribution of final goods and services produced by these businesses accounts for 55.6% of GDP, with added industrial value accounting for 74.7% and exports reaching 62.3%. They are also a vital source of technological advancement. Enterprises have become the primary drivers of innovation in our country, accounting for 65% of patents, achieving over 75% of technological breakthroughs, and developing more than 80% of new products [1].

Additionally, they are the primary avenue for job creation, supplying over 75% of employment opportunities and serving as the principal means of absorbing workforce. However, in recent years, our country's enterprises have faced significant challenges due to ongoing policy shifts. Recent statistics reveal that over the last five years, 70% of small and medium-sized businesses have closed, while 30.81% continue to struggle with financial losses. Research indicates that many enterprises prioritize profit generation at the expense of financial management [2], resulting in a management approach that remains entrenched in traditional production and operational practices. This oversight hampers their ability to leverage the benefits of financial management and risk mitigation fully. Factors such as insufficient funding, an unbalanced capital structure, poor cash flow, lack of financial data, disorganized management, outdated practices, absence of an internal control system, and a limited understanding of risks significantly diminish the capacity of small and medium-sized enterprises to withstand and navigate financial challenges. As a result, it becomes exceedingly difficult for these businesses to sustain and grow. In the face of an increasingly complex market landscape, driven by the knowledge economy and global pressures, small and medium enterprises must accelerate their transformation and growth to align with rising market demands. The financial health of these companies is vital; their effectiveness or deficiencies can significantly impact their sustainable development [3].

As globalization advances, our nation's small and medium enterprises are encountering unprecedented challenges, with their financial pressures mounting daily. This situation could not only adversely affect their operational viability but also inflict substantial harm on the healthy advancement of the global economy and social welfare [4]. Given the complexity and unpredictability of the market, enterprises must thoroughly understand their financial risks, conduct in depth analysis, anticipate potential effects, implement appropriate safety measures, alleviate their burdens, and ensure stable, long-term operations.

Following an extensive theoretical examination, the development of a robust financial risk prediction system will significantly enhance the operational efficacy of businesses in our nation, thereby improving the management, mitigation, reduction, or elimination of financial risks, and allowing enterprises to function in a sustainable, trustworthy, and efficient manner [5].

2. Early Studies

Over the years, the dependability and efficiency of artificial neural network technology have gained widespread acknowledgment, with its progress becoming notably advanced. Recently, the use of neural network technology in economic forecasting and early warning systems has attracted significant interest from researchers worldwide, yielding impressive results. Ding Q's innovative hybrid computation, which integrates neural networks with genetic algorithms, can effectively simulate the exchange rate forecasts for four major currencies over the upcoming 90 days, including the British pound, Deutsche Mark, yen, and Swiss franc, thus accurately detecting shifts in the Renminbi's trends and effectively avoiding substantial fluctuations. Research indicates that AI technology utilizing genetic algorithms can furnish precise financial insights. The three computational methods characterized by classification, presented by WenH: CBFS, ANN, DA, form a comprehensive new algorithm suitable for bankruptcy early warning. Its operational framework involves four stages: training, evaluation, optimization, and final prediction [6]. This research uses the significant economic events that transpired in South Korea from 1991 to 1993 as a foundation, categorising the gathered data into three segments: training, testing, and application for network generalisation. The findings reveal that employing the integrated model can yield favorable forecasting results. However, when this model is extended to other domains, essential adjustments and enhancements must be implemented. The intelligent forecasting system devised by Feng and colleagues, utilizing fuzzy neural network technology, can effectively assist businesses in managing sales variations during promotional efforts [7]. While ANN models can project sales with greater accuracy, they still require substantial refinement and enhancement. Through the application of FNN technology, it was observed that its precision significantly improves when paired with time series data, and the training error of the FNN model employing weight estimation would also see considerable reduction. ANN technology has been extensively utilized across various sectors, with numerous scholars conducting thorough investigations into it. For instance, Meng established an ANN-based economic forecasting and early warning system employing improved BP algorithms [8], which effectively prevents the model from becoming trapped in local optima and significantly accelerates convergence [10]. Kuang et al. applied the BP neural network model to simulate and forecast the macroeconomic landscape of Tianjin City, finding that it greatly enhanced prediction accuracy and more accurately reflected the real situation, far surpassing traditional economic forecasting methods [11]. Kitova et al. developed a comprehensive neural network based economic forecasting indicator system grounded in relevant financial evaluation standards to assess the company's financial well being [12]. It encompasses 15 indicators, of which four are financial ratios. Additionally, BP neural networks were employed to develop a comprehensive corporate financial forecasting model, which was validated through practical case studies. By leveraging cutting edge technology and integrating it with artificial intelligence, we can effectively detect, evaluate, and address corporate financial risks, thereby uncovering potential threats more accurately. Consequently, we have established a risk classification system based on fuzzy optimization techniques that can proficiently identify risks, providing a foundation for implementing more focused and effective risk management strategies [13].

3. Construction of the Corporate Financial Risk Early Warning Model Based on Grey BP Neural Network

3.1 Overview of Related Principles

The BP neural network features a three tier architecture in which the neurons in each layer operate independently, perform distinct tasks, and do not interconnect. This structure enables the model to comprehend better and process complex data, allowing for more precise predictions of unforeseen outcomes [14, 15]. In contrast to conventional models, the BP model offers greater flexibility and can identify the optimal model more swiftly, thus accomplishing tasks more efficiently. The BP neural network integrates the development of a "sample" model with real world results, using a specific simulation model that enables the BP model to grasp essential problem solving concepts. Through training the BP neural network, we can more effectively tackle similar challenges [16]. The layered nature of the BP neural network distinguishes it in the realm of artificial intelligence, and it is also widely utilized in real world applications. Its structure is illustrated in Figure 1. “The network architecture is comprised of three segments: the input layer, the output layer, and the hidden layer. The hidden layer’s hierarchy may vary, but it is typically included. Specific weights interconnect each layer, and there is no coupling between any layers within the entire framework. Interaction among these layers typically uses the Sigmoid function. However, when the processor is in a hidden or visible state, its activation function becomes predominantly linear.

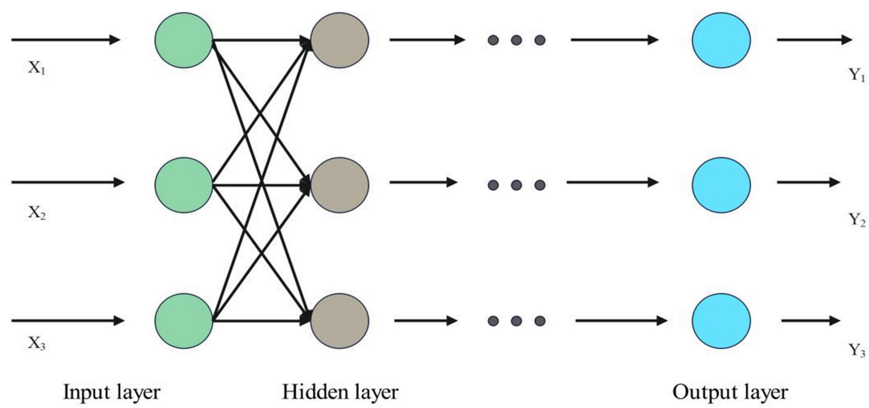

Figure 1. Model structure based on a grey BP neural network

(1) To avoid the network reaching saturation state too early, we need to initialize the weights of all connection weights to smaller random numbers, as shown in formula 1.

$$x_t' = \frac{x_t - x_{\min}}{x_{\max} - x_{\min}} \quad (1)$$

(2) By inputting a designated model, we can compute the network’s output. (3) By assessing the discrepancy between the actual measurement outcomes and the predicted results, we can adjust the weights accordingly. (4) Throughout the training phase, we must continuously repeat the two steps above until the model’s error reaches an acceptable threshold.

3.2 Model Building Ideas Based on Grey BP Neural Network

The examination of the three-layer network revealed that it offers considerable advantages due to its distinct hidden layer, which facilitates the easy attainment of local optima. In contrast, a three-layer network requires multiple hidden layers to model complex systems. Depending on the specific scenarios, the quantity of nodes in the input and output layers is contingent upon the particular issues at hand, and the existing financial statement data can serve as the current window for precisely forecasting future developmental trends. The variable n denotes the current window size, enabling us to predict future developments and accurately prepare for forthcoming changes. Given the limitations of the one-dimensional spatio temporal range, to better replicate the real conditions at time $t+n$, it is essential to add a hidden node in the input layer; however, this addition can effectively reduce the model’s training duration and enhance its generalization and accuracy. Nonetheless, an excessive number of nodes within the network may lead to suboptimal modeling outcomes. Typically, the number of hidden nodes should lie between the numbers of input and output nodes. In this context, X, X_1, X_{-2}, ..., X_{t-1} denote n inputs, X indicates the output, and there are r hidden nodes. Occasionally, we can employ specialized connection techniques to attain greater accuracy within a limited timeframe. This paper introduces a novel model that enables complete information exchange among all networks. This model allows each network to function independently while being accessible to other networks.

$$f(x) = \frac{1}{1+\exp(-x)} \quad (2)$$

To effectively control the neural network's input, we use a linear function to adjust $f(x)$ to achieve optimal performance.

3.3 Selection of Initial Parameters

By setting reasonable parameters, the neural network can quickly and effectively converge, and the error can be controlled within an acceptable range. Its calculation method is: XN-1, the value of sse can be represented by the following formula:

$$SSE = \frac{1}{2}\sum_{k}\left(x_k - \hat{x}_k\right)^2 \quad (3)$$

By using the BP algorithm, we can train the model to get the expected x and the actual output. If the model's accuracy does not meet the preset error threshold, we need to adjust the model to achieve the optimal model.

4. Experimental Design and Result Analysis

4.1 Experimental Design

The BP artificial neural model standardizes 16 indicators from 2000 to 2004 to derive corresponding composite function coefficients for evaluating the model's accuracy. Furthermore, data from 2005 and 2006 were utilized for empirical analysis. In this study, we referenced a BP neural network model designed to evaluate corporate financial risk. This model comprises 16 inputs, 9 hidden nodes, 4 outputs, and can accommodate a deviation of 0.001. We based our training and simulation on the company's financial statements over the past five years. Using trainbpx(), we commenced in 2000 and trained 2194 times with 16 different models to assess the company's financial risk scenario to fulfill accuracy standards. Ultimately, the data from 2005 and 2006 were analyzed to verify accuracy. The BP neural network model we constructed can effectively aid companies in identifying and promptly recognizing potential financial risks. However, relying solely on these indicators can only capture information within a single domain to a limited extent. Therefore, to more effectively evaluate and manage corporate financial risks, it is crucial to integrate multiple factors for a multidimensional assessment. By employing scientific techniques and aligning with the realities of economic activities, we can measure the overall economic performance with greater precision. Specifically, we can scrutinize various economic monitoring indicators, merge relevant statistical analysis methods, and develop a comprehensive index that accurately reflects the current financial landscape.

4.2 Experimental Results and Analysis

Following thorough evaluation, we gathered pertinent indicator data from 93 firms. These firms were categorized into various types, with 58 designated as training models and another 58 as testing models. We further classified these firms into three groups based on their financial status: 30, 18, and 19. Using MATLAB, we trained 7 alerts for 7 companies across 58 distinct categories, and the outcomes are illustrated in Figure 2 to evaluate the training accuracy. This illustration shows that the R value exceeds 0.88944, indicating that the BP neural network's performance has surpassed the initial parameters and aligns with our expectations, thereby confirming its high accuracy and precision. The image clearly demonstrates that the BP neural network's fit meets our criteria, with high accuracy and precision, translating into strong predictive capability.

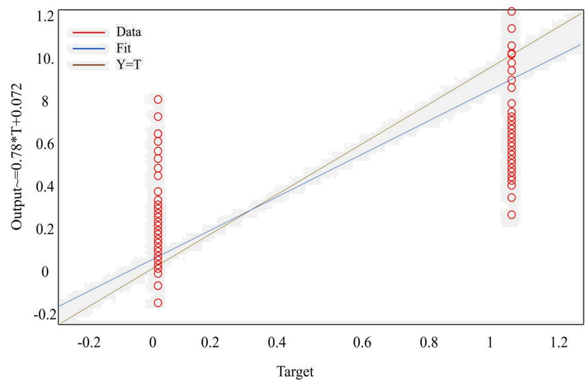

Figure 2. Test Results of the BP Neural Network

As depicted in Figure 2, the model will be activated when the error falls below the anticipated threshold of 6. Furthermore, by varying the number of neurons in the hidden layer to 50, 30, 10, and 5, respectively, the model can achieve higher accuracy. This process allows us to identify a neural network framework suited for this analysis. Once the training phase is complete, we will validate the model by feeding the enterprise indicator data into MATLAB to gauge its accuracy. We will juxtapose the output results with the actual data and compile the findings into charts for the testing outcomes of T-1 and T-2 years as a reference.

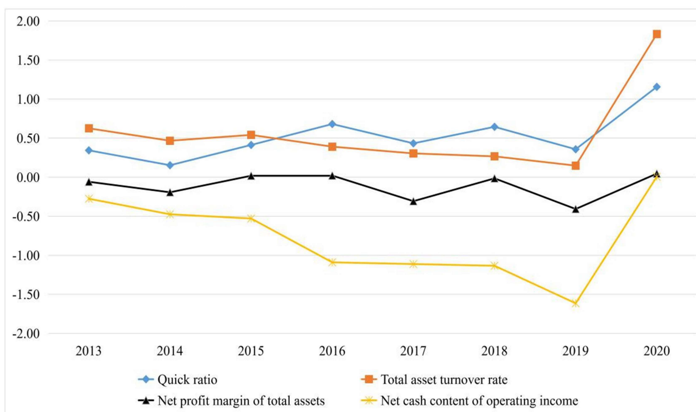

Figure 3. Discrepancies Between Predicted Values and Actual Values

According to Figure 3, the predictive accuracy for T-1 is markedly superior to that of T-2, particularly for firms with weak financial standings, where T-1's accuracy is even greater, reaching levels exceeding two years. This suggests that the financial challenges enterprises face frequently stem from risks inherent to their daily operations, and that these impacts are likely to escalate over time. To mitigate financial risks, companies should implement measures promptly. Based on this research, we concluded that this model can reliably forecast financial conditions over the next two years, especially in relation to the T-year. Additionally, it can offer a broader perspective to assist managers in swiftly recognizing and addressing potential financial crises, ultimately facilitating the long-term stable operation of the enterprise.

5. Conclusion

By utilizing BP neural networks and factor analysis techniques, we have developed a new estimation model aimed at assessing the financial risks associated with companies. This model's strength lies in its ability to identify and evaluate financial risks while remaining user friendly more accurately. The effectiveness of the BP neural network is influenced by various factors, such as the company's financial status and anticipated experiences. One of its benefits is the simplicity required for its data set, which facilitates error identification and correction. Furthermore, the neural network's adaptability enables it to improve performance through self learning and training as additional information becomes available. Consequently, the BP neural network proves to be an exceptionally effective tool for navigating complex economic conditions, particularly for companies in the growth and expansion phase. In specific scenarios, this method even surpasses expectations.

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