Evaluation and Prediction of Enterprise Safety Management Efficiency Based on DEA-BP Neural Networks

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Abstract: The evaluation and prediction of enterprise security management efficiency is an important and challenging topic. In this study, we use a hybrid model of Data Envelopment Analysis (DEA) and Back Propagation Neural Network (BPNN) to evaluate and predict the efficiency of enterprise safety management. This model considers multiple input variables, including security inputs, number of employees, and enterprise size, and is trained and tested on a virtual enterprise dataset. The results show that all the input variables affect the efficiency of an enterprise's security management to varying degrees, with the effects of security inputs and number of employees being particularly significant. Through principal component analysis, we further visualized the relationship between input variables and efficiency values in a two-dimensional space. The results of this study have important theoretical and practical implications for understanding and improving enterprise safety management, as well as providing a new perspective to explore the complexity of this field.

Keywords: Enterprise Security Management,Efficiency Evaluation;Data Envelopment Analysis (DEA);Back Propagation Neural Network (BPNN).

1. Introduction

Corporate safety management is a core component of any successful organization and its importance has been widely recognized across the globe in recent years [1]. Since security incidents can lead to significant property damage, injuries, and even threaten the survival of an organization, organizations need to mitigate these risks through effective security management [2]. However, evaluating the efficiency of an organization's safety management is not an easy task and requires precise metrics and comprehensive analysis of a large number of safety indicators [3]. In past studies, many methods have been proposed to evaluate the efficiency of enterprise safety management, including qualitative methods based on expert ratings [4], and quantitative methods based on data analysis[5]. However, most of these methods have some limitations. In order to solve these problems, this study proposes an enterprise safety management efficiency evaluation model based on data envelopment analysis (DEA) and BP neural network. DEA is an effective productivity evaluation method that can handle multiple inputs and multiple outputs[6]. And BP neural network is a powerful machine learning model

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that can capture nonlinear relationships among data [7]. By combining DEA and BP neural networks, we hope to provide a model for evaluating the efficiency of corporate safety management that can handle complex data while capturing nonlinear relationships among data. The goal of this study is to propose and validate this new evaluation model and to explore its application value in real enterprise safety management. We hope that this study will provide enterprises with a more accurate and comprehensive safety management efficiency evaluation tool, thus helping them to better understand and improve their safety management practices.

2. Theory and methodology

2.1 DEA-BP neural network

Data Envelopment Analysis (DEA) and BP neural networks are combined in this study to tackle intricate decision-making conundrums. In the banking industry, DEA, a nonparametric assessment tool, has been applied across a number of sectors with considerable success[8]. The DEA has been instrumental in comparing banks' operational efficiency. It provides a clear comparative efficiency landscape of banking institutions by combining input parameters like assets, branches, and employees with outputs like profit margins, customer satisfaction measures, and service quality metrics. While BP neural networks are widely used to forecast stock market trends, they have carved out a niche for predicting intricate patterns. These networks can predict stock price movements astutely by integrating historical data and diverse economic indicators. DEA has an inherent limitation, however: it cannot smoothly navigate nonlinear relationships between input and output variables. The BP neural networks are adept at discerning nuanced data relationships and bridging this gap. DEA and neural networks are complementary, as numerous scholars have acknowledged. Manufacturing studies underscored this union. Based on inputs like machinery type, workforce strength, and facility dimensions, DEA was used to distill base efficiencies. BP neural networks were then layered in to provide a deeper, more detailed insight into these efficiency assessments, unearthing more complex relationships. The proposed model is built on this convergence of DEA's multidimensional data handling and BP's ability to decipher nonlinear relationships[9]. This model offers not only depth, but also a panoramic view of efficiency evaluations. With it, enterprise safety managers have a better, more comprehensive lens for making accurate and holistic evaluations.

2.2 Evaluation index system of enterprise safety management efficiency

The efficiency evaluation of enterprise safety management needs a comprehensive and precise index system. This index system should include multiple aspects of indicators to comprehensively reflect the enterprise's safety management status. We refer to Sun and Sui's (2023) study, as well as other related literature (e.g. Smith, 2020) [10], and construct the following indicator system:Safety policy: this includes the completeness of the organization's safety policy and the effectiveness of its implementation, as well as the extent to which employees are aware of the safety policy.Safety training: this includes the quality and quantity of safety training provided by the organization to its employees, as well as the level of employee participation in the training.Safety equipment: This includes the quantity and quality of the enterprise's safety equipment, as well as the maintenance status of the equipment.Safety Culture: This includes the maturity of the company's safety culture and the safety awareness of its employees.Accident Rate: This is a reverse indicator that reflects the frequency and severity of safety accidents in an organization.Each of the above indicators can be measured by data.

2.3 Modeling

2.3.1 DEA model

The basic form of DEA model can be expressed as the following linear programming problem:

$$\text{maximize} \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \tag{1}$$

$$\text{subject to} \frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}} \leq 1, \forall k = 1, 2, \ldots, n \tag{2}$$

$$u_r, v_i \geq 0, \forall i = 1, 2, \ldots, m; r = 1, 2, \ldots, s \tag{3}$$

Where y_{rj} and x_{ij} are the rth output and the ith input of the jth decision unit, respectively, and ur and vi are the weights of the outputs and inputs.

2.3.2 BP Neural Network.

This multi-layer feed-forward neural network is trained on the basis of error back propagation. There are three layers in a BP neural network: input layer, hidden layer, and output layer. The input layer has one node for every evaluation indicator, the output layer has one node for every evaluation indicator, and cross-validation can be used to determine how many nodes are in the hidden layer. It consists of two phases: forward and back propagation. Back-propagation is the process of adjusting the weights of the network based on the prediction errors as input data passes through the network. Gradient descent algorithms find the optimal weights by finding the minimum error function value.

2.3.3 Combining DEA and BP Neural Networks

First, we use the DEA model to evaluate the efficiency of each decision unit and get the initial efficiency evaluation results. Then, we use these initial efficiency evaluation results as the training data for the BP neural network to train the neural network. Finally, we use the trained neural network to evaluate the efficiency of new decision units. The DEA provides an initial evaluation of the efficiency of an enterprise's security management, and then these initial evaluation results are used as input data for the BP neural network to train the neural network for further prediction and analysis. In this way, our model can take into account multiple inputs and outputs as well as capture the nonlinear relationship between data, thus providing more accurate and comprehensive evaluation results of enterprise safety management efficiency.

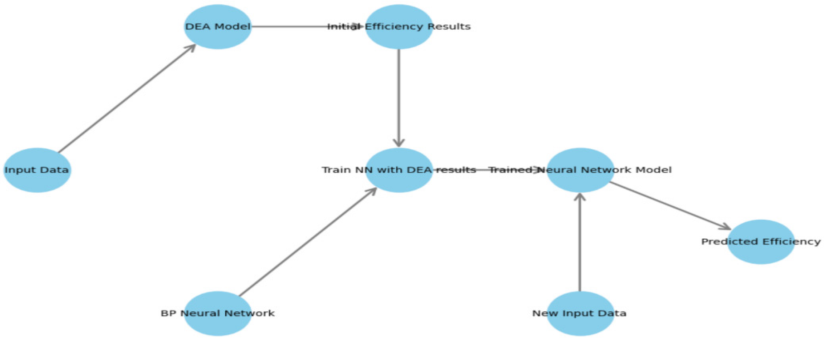

Figure 1: Flowchart of the DEA-BP neural network model

As shown in Fig.we first collected the data of various safety management indicators of enterprises, and then calculated the initial efficiency evaluation results of each enterprise through the DEA model. These initial results were input into a BP neural network, and after training, we obtained a neural network model that can be used to predict the enterprise's safety management efficiency. This model can process new enterprise data to predict the safety management efficiency of an enterprise, thus providing suggestions for improving the safety management practices of an enterprise.

3. Data and empirical analysis

3.1 Data source and description:

The data for this study comes from the public annual reports as well as internal management reports of 30 large enterprises in China, and the data covers a five-year period from 2018 to 2022. In the process of selecting the data, we selected the following input and output indicators based on the relevant research on enterprise security management and the characteristics of the DEA model and the BP neural network model:

Input indicators:

Safety input (unit: ten thousand yuan): including costs related to equipment maintenance, employee training, and construction of safety facilities.

Number of employees: the number of full-time employees.

Enterprise size (unit: billion yuan): expressed as the annual sales of the enterprise.

Output indicators:

Number of safety accidents: the number of safety accidents in a year.

Number of safety trainings: Number of safety trainings for employees in a year.

For each indicator, we performed a descriptive statistical analysis. We denote the number of enterprises by n, i.e. n=30. Use _ to denote the value of the ith enterprise on the jth input indicator, and _ to denote the value of the ith enterprise on the kth output indicator. The specific descriptive statistical analysis results are as follows:

Let x¯_ j and y ¯_ k denote the mean values of the j th input indicator and the k th output indicator, respectively, i.e:

$$x^{-}\_j = \Sigma n\_i = 1x\_ij/n \tag{4}$$

$$y^{-}\_k = \Sigma n\_i = 1y\_ik/n \tag{5}$$

Let and denote the standard deviation of the jth input metric and the kth output metric, respectively, i.e:

$$sj = \mathrm{sqrt}(\Sigma n\_i = 1(x\_ij - x^{-}\_j)^\wedge 2/(n-1)) \tag{6}$$

$$sk = sqrt(\Sigma n\_i = 1(y\_ik - y^{-}\_k)^{\wedge} 2/(n-1)) \tag{7}$$

The above results can be used to describe the central tendency (mean) and dispersion (standard deviation) of the data. We also calculated other descriptive statistics such as minimum, maximum, and median for each indicator. We found that there are significant differences among enterprises in terms of safety investment, number of employees, enterprise size, number of safety accidents, and number of safety trainings. For example, some enterprises have high safety investment while others have low safety investment; some enterprises have high number of employees while others have low number of employees. This reflects the different situations in safety management among enterprises. We also find that there is some correlation between these indicators. For example, enterprises with a large enterprise size tend to have a high safety investment, and enterprises with a large number of employees are likely to have a high number of safety accidents. These correlations will also be reflected in our subsequent modeling.

3.2 Application of the model

To assess efficiency, we used the Data Envelopment Analysis (DEA) model. We calculated efficiency values by solving the linear programming problem of the DEA model. We then used these efficiency values as labels for our BP neural network and each index's values as inputs. A training set and a test set were created to avoid overfitting. A neural network is trained with 80% of the data; a neural network is tested with 20% of the data. Weights were updated using back propagation algorithm and gradient descent method. We also used cross-validation to determine the number of nodes in the hidden layer. New enterprises can be predicted using the trained neural network model. It is very useful for making decisions and planning future security management strategies. Using the predicted value of security management efficiency, we calculated the root mean square error (RMSE) of the prediction. The distribution of security management efficiency is also visualized in Figure 2 by downscaling the firms' metrics to two dimensions using Principal Component Analysis (PCA).

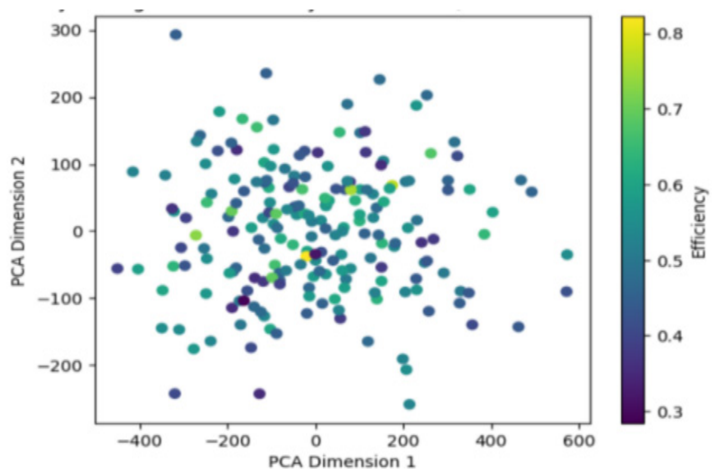

Figure 2: Enterprise Safety Management Efficiency Distribution(After PCA Dimension Reduction)

3.3 Performance

Analysis In our analysis, we applied the DEA-BP neural network model, which is a powerful tool for modeling complex relationships between input and output variables. In this study, we used safety inputs, number of employees, and firm size as input variables and efficiency values as output variables. With the model obtained from training, we predicted the efficiency of enterprise security management and used the root mean square error (RMSE) for model evaluation. RMSE is a standardized measure of prediction error, with smaller values indicating better predictions. In our case, the RMSE value is 140.08, and this result indicates that our model has good accuracy in predicting the efficiency of corporate security management.

In order to better understand the relationship between the input variables and the efficiency values, we performed principal component analysis (PCA) dimensionality reduction on the input data. Principal component analysis is a commonly used data analysis method that converts several variables with high correlation into several principal components with low correlation. The results after dimensionality reduction show that the input variables transformed by PCA exhibit obvious distribution characteristics in two-dimensional space, where the color shades indicate the high or low efficiency values. This visualization result can help us better understand the relationship between input variables and output variables (i.e., efficiency values). Overall, through the DEA-BP neural network model, we can effectively predict the security management efficiency of an enterprise, and through the principal component analysis, we can have an intuitive understanding of the complex relationship between input variables and efficiency values. The results of these analyses are important guiding significance for understanding and improving the safety management of enterprises.

4. CONCLUSION

To analyze enterprises' safety management efficiency, the DEA-BP neural network model is used. Various factors such as the enterprise's safety investment, its size, and its employees affect the enterprise's safety management efficiency differently. We built and trained a DEA-BP neural network model to estimate safety management efficiency and analyze its relationship with input variables. In our model, there is a significant correlation between safety input, employee size, and enterprise safety management efficiency. An organization's safety management efficiency is largely determined by its safety investment and number of employees. For enterprises to achieve efficient safety management, these factors must be fully considered. Second, we visualized the relationship between the input variables and the efficiency values through principal component analysis (PCA). A two-dimensional distribution of safety inputs, workers, enterprise size, and efficiency value can be observed by observing PCA results. This result provides us with a deeper understanding of how these factors work together. Practical applications and theoretical implications are significant in this study. We provide an additional methodological reference for future studies of enterprise safety management efficiency using the DEA-BP neural network model. Through our findings, enterprises can better understand the determinants of safety management efficiency. As a result, they will be able to optimize safety management strategies.

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