

Research on the Innovation Capability Evaluation of Science and Technology-Based Large and Medium-Sized Enterprises Based on the Artificial Neural Network Under Coupling Weights

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ABSTRACT

Science and technology innovation capability is the core competitiveness for the long-term development of science and technology-based enterprises. In this paper, we construct an evaluation system of innovation capability of science and technology-based large and medium-sized enterprises by taking listed science and technology-based enterprises in Jiangsu Province in China's Shanghai and Shenzhen A-shares. The coupling method of AHP subjective assignment and CRITIC objective assignment is used to assign weights to the indicators, and the data are subjected to ANN training to find the best neural network structure, so as to achieve the evaluation of innovation capability of science and technology-based large and medium-sized enterprises. The results show that the growth rate of R&D expenses and the number of invention patent applications are the most important. R&D investment and innovation output are more important. This study uses quantitative methods to evaluate the innovation ability of large and medium-sized scientific and technological enterprises, providing enterprises with a reality evaluation and decision-making basis, with certain guiding significance.

Keywords: AHP; CRITIC; ANN; Technology-based Enterprises; Innovation Capability; Evaluation Study

1. INTRODUCTION

Science and technology-based enterprises are the backbones of enterprises with high technological barriers, their core competitiveness and continuous innovation ability. In 2019, the Ministry of Science and Technology issued "Several Policy Measures on Supporting Science and Technology-based Small and Medium-sized Enterprises to Accelerate Innovation Development in the New Era", considering the ability to innovate in science and technology as the competitiveness of enterprises that cannot be defeated. As a result, it is necessary to accurately evaluate the innovation capability of enterprises and establish a technology-based innovation capability evaluation system to help guide the development of enterprises.

Numerous scholars have done a lot of research work on evaluating the innovation capability of technology-based enterprises. Zhao Wenyan et al [1] established a three-level evaluation index system from seven aspects:

innovation input, research and development, innovation production, innovation output, innovation marketing, management innovation and system innovation, and used expert scoring and AHP method to decompose the index system layer by layer and determine the weight of each index of innovation capability; Sun Liyuan et al [2] added enterprise innovation risk into the innovation capability evaluation system, and designed a combination of qualitative and quantitative indicators Liu Jibing et al [3] used the AHP method to measure and analyze the weight of each factor in the index system, starting from the formation of innovation capability and the way it works; Li Suying et al [4] used quantitative factors to design an evaluation model, providing a new perspective for the evaluation of innovation capability of science and technology-based SMEs; Xiong Peng et al [5] believed that the main factors affecting the innovation capability of regional enterprises are foreign direct investment, high-tech zone enterprise technology income, internal expenditure on science and technology activities and other factors

The literature [1] does not design indicators of enterprise operation status, which is difficult to objectively evaluate the current situation and future development of enterprises; literature [2], although it talks about the combination of qualitative and quantitative, the evaluation system is confusing and weak in practicality; the literature [3] considers the combination of internal and external, but some indicators are difficult to quantify; the literature [4] has taken a quantitative indicator system, but the subjectivity brought by the AHP method cannot be eliminated. Based on the evaluation system of innovation ability of scientific and technological small and medium-sized enterprises in Li Su's literature [4], this paper designs a relevant evaluation system, selects indicators from five aspects of scientific research input, research and development, innovation output, marketing and innovation guarantee, adopts AHP and CRITIC coupling method to calculate indicator weights and combines with ANN model, finally constructs the innovation capability evaluation model of science and technology-based enterprises.

2. EVALUATION SYSTEM OF INNOVATION CAPABILITY OF LARGE AND MEDIUM-SIZED ENTERPRISES IN SCIENCE AND TECHNOLOGY

In order to be able to make a scientific and effective evaluation of the innovation capability of science and technology-based large and medium-sized enterprises, uphold the principles of science, comprehensiveness and reliability, combined with the own characteristics of Jiangsu PV enterprises in Shanghai and Shenzhen A-shares for the selection of indicators. With reference to the innovation capability evaluation indexes of science and technology-based SMEs proposed by literature [4], 15 indicators are selected to build the innovation capability evaluation system of science and technology-based large and medium-sized enterprises by starting from five aspects of scientific research input, research and development, innovation output, marketing and innovation guarantee, as **Table 1** shown.

Table 1 Indicators for evaluating the innovation capacity of medium and large technology-based enterprises

| | Level I Indicators | Secondary Indicators |
|--|--|--|
| Innovation capacity of science and technology-based large and medium-sized enterprises A | Research input capacity B ₁ | Investment intensity of R&D costs C ₁ |
| | | R&D staff input intensity C ₂ |
| | | R&D investment intensity C ₃ |
| | Research and development capacity B ₂ | R&D cost growth rate C ₄ |
| | | R&D expenses to total profit ratio C ₅ |
| | | Number of inventions owned C ₆ |
| | | Number of invention patent applications C ₇ |
| | Innovation output capacity B ₃ | Number of software copyright registration C ₈ |
| | | Percentage increase in earnings C ₉ |
| | | Marketing staff weighting C ₁₀ |
| | Marketing capacity B ₄ | Marketing intensity C ₁₁ |
| | | Marketing stability C ₁₂ |
| | Innovation safeguards capacity B ₅ | Gearing ratio C ₁₃ |
| | | Total asset turnover ratio C ₁₄ |
| | | Return on net assets C ₁₅ |

A) Research input capacity indicators: R&D investment is the necessary guarantee for enterprises to obtain innovation capacity, and it is also the primary power source for forming innovation capacity. Research investment capacity can be divided into financial and human resources. The research investment indexes constructed in this paper include R&D cost investment

intensity C₁, R&D personnel investment intensity C₂ and R&D investment revenue ratio C₃.

B) Research and Development (R&D) capability indicators: The research and development capability are crucial to an enterprise, as it is far from being an innovative enterprise without developing new products and technologies. The R&D capability is the hard power

of the enterprise, and the complex nature of innovation itself makes it difficult to quantify, and the patent data can avoid the bias of estimation due to the error of indicator measurement [7]. In this paper, the indicators of R&D capability include the growth rate of R&D expenditure C_4 , the ratio of R&D expenditure to total profit C_5 and the number of patents owned C_6 .

C) Innovation output capability indicators: Innovation output is the final presentation of R&D results, which is the most intuitive reflection of enterprise innovation capability. The innovation output capability includes both technology and profit, and the innovation output capability indicators constructed in this paper include the number of invention patent applications C_7 , the number of software copyright registration C_8 and the percentage of revenue growth C_9 .

D) Marketing capability indicators: marketing activities are necessary to sell products and technologies to the end of the company, and it is challenging to form significant revenue with quality products and good technologies without marketing. The marketing capability indicators constructed in this paper include marketing staff share C_{10} , marketing intensity C_{11} and marketing stability C_{12} .

E) Innovation security capacity indicator: innovation security is more about the enterprise's financial situation. Only when a company has a good financial environment can it carry out continuous innovation activities [9] and guarantee its better development with strong strength. This paper's innovation security capacity indicators include gearing ratio C_{13} , total asset turnover ratio C_{14} and return on net assets C_{15} .

3. COUPLING WEIGHTS OF INNOVATION CAPABILITIES OF MEDIUM AND LARGE TECHNOLOGY-BASED ENTERPRISES

3.1. AHP subjective weights

Hierarchical analysis (AHP) was proposed by Professor T.L. Saaty [10], which is a systematic and hierarchical method of analysis that combines qualitative and quantitative approaches. When using hierarchical analysis to construct a system model, it can be broadly divided into four following steps.

Step1: Build a hierarchical model. It includes the target layer, guideline layer and program layer.

Step2: Construct the judgment (pairwise comparison) matrix. Start from the second level with pairwise comparison matrices and scales 1 to 9.

Step3: Hierarchical single ordering and its consistency test. For each pairwise comparison matrix, the maximum eigenvalue and its corresponding eigenvector are calculated, and the consistency test is done using consistency index, random consistency index

and consistency ratio. If the test passes, the eigenvectors (after normalization) are the weight vectors; if not, the pairwise comparison matrices need to be reconstructed.

Step4: Hierarchical total ordering and its consistency test. Calculate the weight vector of the bottommost level to the topmost level total ordering. Use the total ranking consistency ratio to perform the test. If it passes, the decision can be made according to the result expressed by the total ranking weight vector. Otherwise, the model needs to be reconsidered, or those pairwise comparison matrices with larger consistency ratio CR need to be reconstructed.

3.2. CRITIC objective weights

Conflicting correlation among criteria (CRITIC) method was proposed by Diakoulaki [11] as an objective weighting method. He believes that two factors determine the weight of evaluation indicators, one is the standard deviation, which reflects the degree of variation in the values of evaluation indicators; the other is the correlation coefficient, if there is a strong positive correlation between two evaluation indicators, it means that the two indicators are less conflicting; if there is a strong negative correlation, it means that the two indicators are more conflicting [12]. The basic principle of CRITIC method is:

$$C_j = \sigma_j \sum_{i=1}^n (1 - r_{ij}) \quad (1)$$

Where C_j denotes the degree of influence of the j -th evaluation index on the system, σ_j denotes the standard deviation of the j -th evaluation index, and r_{ij} denotes the correlation coefficient between the i -th evaluation index and the j -th evaluation index. The larger the value of C_j , the greater the degree of influence of the j -th evaluation index on the system, and the greater the relative importance of the index, thus the objective weight ω_j of the j -th evaluation index is calculated as follows:

$$\omega_j = \frac{C_j}{\sum_{j=1}^n C_j} \quad (2)$$

3.3. Coupling weights

The traditional methods of determining weights are all influenced to some extent by subjective and objective factors. In this paper, we use AHP method to determine subjective weights and CRITIC method to determine objective weights to get combination weights. The function is constructed according to the principle of

minimum relative information entropy [9].

$$F = \sum_{i=1}^2 \sum_{j=1}^n W_j (\ln W_j - \ln W_{ij}) \quad (3)$$

where $\sum_{j=1}^n W_j = 1, W_j > 0$. W_{1j} is AHP subjective weight and W_{2j} is CRITIC objective weight. The optimal solution is solved using the Lagrange multiplier method i.e. the combined weights are:

$$W_j = \frac{\sqrt{W_{1j}W_{2j}}}{\sum_{j=1}^n \sqrt{W_{1j}W_{2j}}} \quad (4)$$

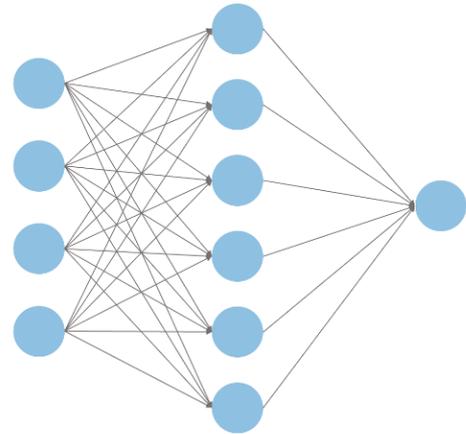
The overall evaluation score is:

$$F_i = \sum_{j=1}^n Y_{ij} \cdot W_j \quad (5)$$

4. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANN) are numerical and mathematical models that simulate the human brain's neural structure and have several advantages over other statistical regression methods [13]. First, the main features of artificial neural networks are that they do not require a predetermined mathematical relationship for mapping between inputs and outputs, and they can reproduce complex nonlinear input-output relationships and be applied to sequential training processes. Moreover, due to their high degree of self-organization, adaptability and self-learning capabilities, artificial neural networks can successfully implement distributed storage and parallel information processing.

The network combines a synaptic hierarchical framework consisting of an input layer, one or more hidden layers, and an output layer. The general topology of the three-layer neural network is Figure 1 shown. Each layer consists of multiple artificial neuronal elements, often called neurons. The combination of signals from the neurons in the previous layer is received by the neurons in the next layer, and the signals are transformed by an activation function. Weighted connections between the neurons send the output of the neurons of the previous layer to the input of the neurons of the next layer. The main function is to extract knowledge from the training data and store the learned knowledge as the weights of the connections.



Input layer Hidden layer Output layer

Figure 1 Three-layer neural network

Figure 2 shows the working mechanism of neurons in a typical artificial neural network structure, which is the same as Figure 1, three-layer neural network.

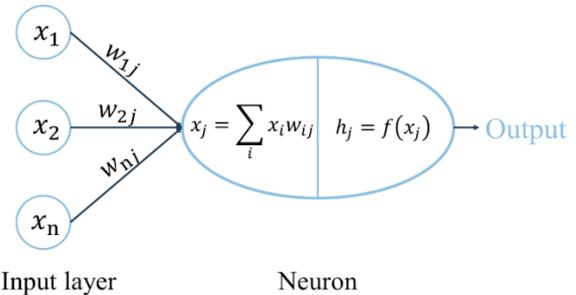


Figure 2 Mechanisms of neuronal work

During artificial neural network training, each neuron in the input layer receives data and multiplies these values by the appropriate weights; the results are then passed to the hidden layer. In the hidden layer, each neuron receives the transmitted activation signal from the previous layer and generates the output signal through the activation function. The activation signal is a weighted sum of all signals entering the neuron and can be expressed as:

$$x_j = \sum_i x_i w_{ij} \quad (6)$$

Where x_i is the input to the input layer, w_{ij} is the weight vector between the input layer and the hidden layer; x_j is the neuron, j is the activation signal received in the hidden layer. The neurons in the hidden layer generate the output signal through the activation function. The activation function of the hidden layer has various forms.

5. RESEARCH ON THE EVALUATION OF INNOVATION CAPABILITY OF SCIENCE AND TECHNOLOGY-BASED LARGE AND MEDIUM-SIZED ENTERPRISES BASED ON THE ARTIFICIAL NEURAL NETWORK UNDER COUPLING WEIGHTS

5.1. Subject study and data collection

The photovoltaic industry is an important segment of the new energy industry. Under the dual role of policy guidance and market drive, China's PV industry has developed rapidly in recent years [14]. As Jiangsu province is a vital PV industry gathering area [15], this paper screens 27 Jiangsu companies in the PV sector of

China's Shanghai and Shenzhen A-shares, and obtains specific data on 15 indicators of the companies from 2018-2020 through the company's financial statements and collates them.

5.2. ANN Training

The data was trained as a neural network using SPSS 26.0 with one hidden layer, 70% of the training set and 30% of the test set, and the training process was achieved by varying the number of units in the hidden layer. Considering the fitting accuracy, the number of hidden layer units starts from 10. When the number of hidden layer units is 10, the training results begin to converge. The specific training is shown in the following table.

Table 2 Neural network training results

| Number of hidden layer cells | Training 70% | | Test 30% | | Predicted versus observed values |
|------------------------------|---------------|----------------|---------------|----------------|----------------------------------|
| | squared error | relative error | squared error | relative error | MSE |
| 10 | 0.606 | 0.022 | 1.123 | 0.082 | 0.000175 |
| 11 | 0.296 | 0.009 | 1.791 | 0.082 | 0.000166 |
| 12 | 0.209 | 0.007 | 0.165 | 0.034 | 0.000046 |
| 13 | 0.062 | 0.002 | 0.266 | 0.047 | 0.000045 |
| 14 | 0.198 | 0.006 | 0.115 | 0.043 | 0.000039 |
| 15 | 0.092 | 0.003 | 5.770 | 0.185 | 0.000414 |
| 16 | 1.464 | 0.055 | 1.272 | 0.106 | 0.000300 |
| 17 | 0.052 | 0.002 | 2.207 | 0.138 | 0.000239 |
| 18 | 0.043 | 0.001 | 0.457 | 0.031 | 0.000048 |
| 19 | 0.045 | 0.002 | 1.393 | 0.159 | 0.000161 |
| 20 | 1.222 | 0.043 | 0.419 | 0.066 | 0.000196 |
| 21 | 0.582 | 0.020 | 0.164 | 0.030 | 0.000093 |
| 22 | 0.023 | 0.001 | 2.176 | 0.134 | 0.000226 |
| 23 | 0.202 | 0.009 | 12.364 | 0.422 | 0.000991 |
| 24 | 0.168 | 0.006 | 0.254 | 0.110 | 0.000056 |
| 25 | 0.377 | 0.015 | 0.784 | 0.156 | 0.000163 |
| 26 | 0.762 | 0.027 | 2.127 | 0.126 | 0.000266 |
| 27 | 0.488 | 0.017 | 0.503 | 0.036 | 0.000096 |
| 28 | 0.048 | 0.002 | 0.882 | 0.062 | 0.000102 |
| 29 | 0.392 | 0.014 | 1.398 | 0.104 | 0.000179 |
| 30 | 0.019 | 0.001 | 1.613 | 0.072 | 0.000143 |

Evaluating machine learning algorithms allows comparing the performance of different algorithms. The mean square error (MSE) is the expected value of the square of the difference between the parameter estimate and the true value of the parameter and is the most widely used, so the mean square error is chosen to measure the

algorithm accuracy. By observing the neural network training, it is found that: when the number of hidden layer units is 14, the mean square error between the predicted and observed values is the smallest, so the number of hidden layer units 14 is chosen as the best neural network structure. From Figure 3, it can be seen that the output

value and the predicted value are basically on a straight line of $y=x$, which indicates that the network is well trained.

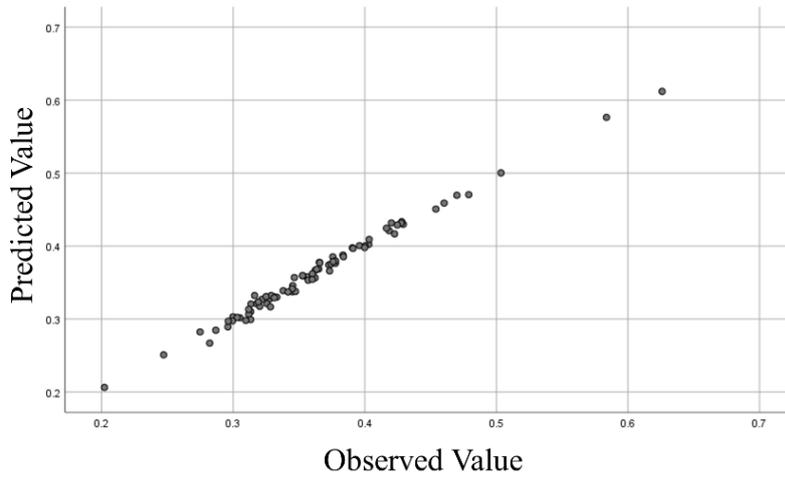


Figure 3 Predicted-actual graph

5.3. Analysis of the importance of independent variables

By training the neural network with the number of

hidden layer units from 10 to 30, the number of hidden layer units 14 was selected as the best neural network structure, and the importance analysis plot of independent variables was obtained, as shown in Figure 4.

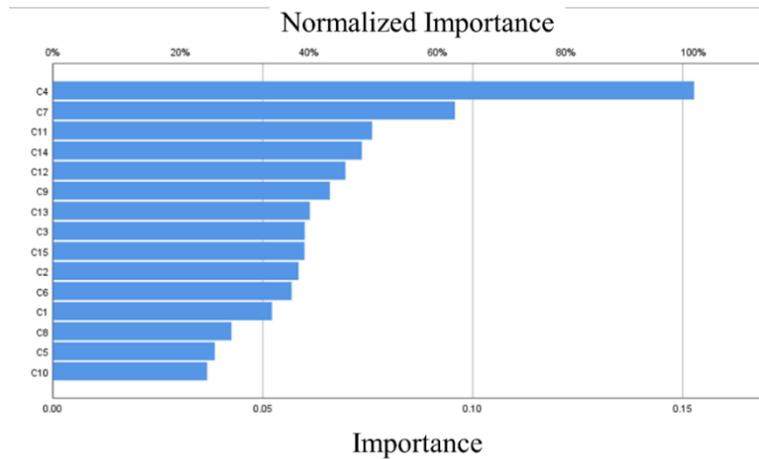


Figure 4 Importance of independent variables

As shown in Figure 4, the percentage of C₄ R&D expense growth rate exceeds 100%, the percentage of C₇ invention patent applications is about 60%. The percentage of C₁₁ marketing intensity, C₁₄ total asset turnover ratio, C₁₂ marketing stability, C₉ revenue growth is about 40% to 50%, the percentage of C₁₃ gearing ratio, C₃ R&D investment intensity, C₁₅ return on net assets, C₂ R&D personnel investment intensity, C₆ invention patent ownership, C₁ R&D expense investment intensity is relatively average, basically stable at around 40%, and the number of software copyright registrations C₈, R&D expense to total profit ratio C₅, and marketing staff ratio C₁₀ are all below 40%.

Therefore, technology-based enterprises should pay more attention to the investment in research and development costs, and deeper research and development of products and technologies. Mastering core technology

is not only the guarantee of the strength of technology-based enterprises, but also an important embodiment of innovation capacity. At the same time, pay attention to the use of marketing means to enable companies to obtain greater profits, so as to better reinvest and research and development, and achieve a good innovation cycle. It is worth noting that the number of software copyright registrations and the proportion of marketing personnel are not of high importance, indicating that technology-based enterprises need to sink their hearts more into the research and development of core products and technologies, and marketing planning in non-personnel marketing is sufficient. Technology-based enterprises need to perpetuate their innovative vitality to promote the industry's good development, which brings high profits to enterprises and benefit people's lives.

6. CONCLUSION

(1) The best neural network structure: when the hidden layer is one layer, and the number of hidden layer units is 14, the relative errors of training set and test set are less than 0.05, and the mean square error of predicted value and observed value is the smallest, and the accuracy is high, so the structure is the best neural network structure. Thus, the best neural network structure suitable for evaluating the innovation ability of science and technology large and medium-sized enterprises can be constructed, which is of great practical value and guiding significance.

(2) Important factors affecting the development of technology enterprises: by looking at the importance graph of independent variables, C_4 the percentage growth of R&D expenses is the most important, and C the number of invention patent applications₇ is the second most important, which shows that R&D investment and patents are the biggest driving force for the development of large and medium-sized technology enterprises; C_{11} marketing intensity, C_{14} total asset turnover, C_{12} marketing stability, and C_9 the percentage growth of revenue are not similar in importance, which shows that the marketing and profitability are also critical to innovation capability. It can be seen that the company's own strong financial strength is not the main expression of innovation ability, but should be expressed in the growing investment and innovation and complemented by marketing tools. In terms of indicators, research and development capability and innovation output capability are the most important, followed by marketing capability, while research input capability and innovation guarantee capability are relatively weaker.

(3) Policy advice: For enterprises, enterprises should increase R&D investment, continuously develop new products, new technologies, and improve innovation results. For the country, we should strengthen the multidisciplinary application for scientific and technological enterprises, and strengthen the subsidies to science and technology enterprises to maximize the effectiveness of the achievements.

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