# Predicting the Growth Value of Technology Enterprises with an Optimized Back-Propagation Neural Network

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**Keywords:** back-propagation, technology-based small and medium-sized enterprises, development value, particle swarm optimization

**Received:** June 19, 2024

*Accurate assessment of the development value of technology-based small and medium-sized enterprises (SMEs) is beneficial to the effective support of these enterprises. This paper briefly introduced technology-based SMEs and factors affecting their development values. Then, the development value of enterprises was evaluated using a back-propagation neural network (BPNN) algorithm. The BPNN algorithm was improved by particle swarm optimization (PSO). The specific improvement method was using particles in the PSO to represent adjustable parameters in the BPNN algorithm. Each particle represented a parameter scheme, and during the training of the improved BPNN, the iteration of the particle swarm in the PSO was used to replace reverse parameter adjustment based on training error. Finally, the PSO-BPNN algorithm was simulated and compared with the extreme learning machine (ELM) and traditional BPNN algorithms. The results showed that the ELM quickly obtained the weight parameters by generalized inverse matrix. The PSO-BPNN algorithm had faster convergence than the traditional BPNN algorithm in training. The former converged to stability after about 600 iterations, while the latter converged to stability after about 800 iterations. Moreover, the improved BPNN algorithm had a smaller mean square error after stabilization. The PSO-BPNN algorithm had the smallest calculation error for the development value assessment number (1.00%-1.25%) and correlated significantly with the market value growth rate (P = 0.002). The PSO-BPNN algorithm can effectively evaluate the development value of technology-based SMEs.*

*Povzetek: Izboljšan je model BPNN, optimiziran z algoritmom rojev delcev (PSO), za napovedovanje vrednosti razvoja tehnoloških malih in srednje velikih podjetij. Rezultati kažejo, da je PSO-BPNN hitreje konvergiral in imel manjše napake v primerjavi s tradicionalnim BPNN, kar omogoča učinkovito oceno razvojne vrednosti podjetij s tehnološko usmeritvijo.*

## 1 Introduction

The economy's swift progress has pulled a large number of enterprises to develop, not only increasing in size but also in number. However, even if the market size gradually increases, it is limited. Large enterprises can earn a place in the growing market relatively easily with their advantages and capital accumulated over the years [1], but for small and medium-sized enterprises (SMEs), the capital they have accumulated is not enough to obtain market share quickly. Therefore, SMEs need to have enough characteristics to be unique in the business battle and enhance their core competitiveness [2]. Technology-based enterprises place a greater emphasis on the research and development of technology than traditional enterprises, and their characteristic in the business competition is technological innovation. Technology-based enterprises not only provide jobs for society as traditional enterprises do but also have the technology to promote the innovative development of the country. In addition, although technology-based companies are competitive in the market with their innovative technologies, they have little accumulation and do not have the advantage in terms of sustainable operations. For job creation and technological innovation, the state supports technology-based SMEs [3] to enable them to survive the growth period. Many technology-based SMEs are established every year, and many die in the development process. Once the supported SMEs die, the previously invested support resources will be wasted. Therefore, to maximize the effect of the support resources, the development value assessment is carried out before supporting technology-based SMEs, and the support resources are tilted to the technology-based SMEs with higher development values [4]. Accurate assessment of the development value of technology-driven SMEs is beneficial in maximizing the use of support resources. The related studies are reviewed in Table 1. These studies have all discussed the economic growth of enterprises and used different methods. This paper used the back-propagation neural network (BPNN) algorithm in deep learning to evaluate and forecast the development value of technology-based enterprises. To improve the predictive performance of the BPNN algorithm, particle swarm optimization (PSO) was selected as a replacement for the traditional back-propagation parameter adjustment-based training method. Each particle in the PSO swarm represented a parameter scheme for the BPNN algorithm. During the training of the BPNN algorithm, the PSO swarm was iterated based on the training error of the BPNN algorithm under each particle's parameter scheme until the training error converged to stability. The present study utilized the PSO method to avoid the problem of local optima caused by the traditional training approach in the BPNN algorithm, where parameters are adjusted step by step based on errors. However, it should be noted that PSO may also encounter the issue of getting trapped in local optima. Therefore, future research should focus on minimizing the risk of BPNN training falling into local optima.

Table 1: Related studies

| Author | Research content | Result |
|---|---|---|
| Omeke et al. [5] | They investigated the role of networks in mediating the connection between the growth of financial cooperatives and their dynamic capabilities using a structural equation model | Dynamic capabilities were essential to promote the growth of financial cooperatives. |
| Chen et al. [6] | They assessed the green growth efficiency of businesses across 31 Chinese regions in the years 2003, 2007, and 2012 using the super-efficiency data envelopment analysis (DEA) model. | There were significant regional differences the green growth efficiency of Chinese enterprises in the three years. |
| Fan et al. [7] | They proposed the utilization of the distance from average solution approach for aggregating ultimate cross-efficiency scores in order to select the best technology. | The approach was verified through a case study. |

# 2 An algorithm based on optimal BPNN for predicting the development value of technology-based SMEs

## 2.1 Technology-based SMEs and the factors affecting development value

A technology-based SME is a classification of SMEs, which is a concept relative to large enterprises. Such enterprises are weaker in the market competition because they are far inferior to large enterprises in terms of employee size and market revenue. Technology-based SMEs pay more attention to the advancement and growth of technology than general SMEs and place more emphasis on investment in technology research and development in market competition and enterprise development [8]. The output of these SMEs has a higher technological content and a higher proportion of intangible assets. Their demands for human resources are great, and most of their revenue comes from the productivity that innovative technology translates into. Although the returns are high, the conversion process has a high risk.

Technology-based SMEs can achieve high returns in the market with innovative technologies, but they also face high risks in the process of converting technologies into returns. Supporting technology-based SMEs in the early stages of development can enhance their resistance to risks. A large number of similar SMEs with varied development qualifications are established annually. There is a risk of failure even if support is provided. Therefore, in order to maximize the role of support resources, the development value of enterprises needs to be assessed [9].

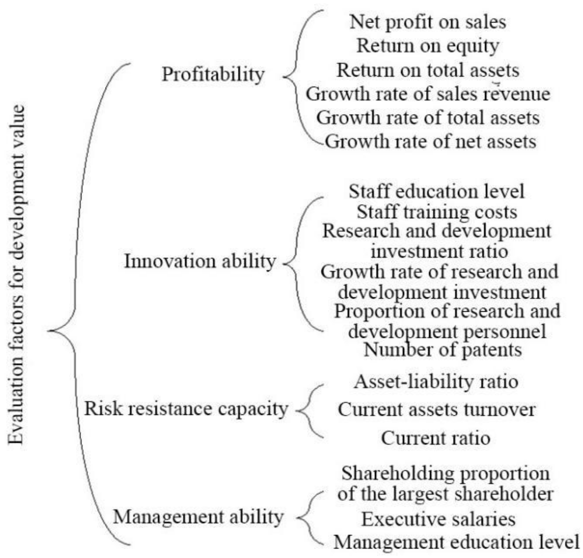


Figure 1: Schematic diagram of the factors used to assess the development value of technology-based SMEs

Figure 1 shows a diagram of the factors used to assess the development value of a company. Among them, profitability, risk resistance, and management capacity are the major factors required to evaluate a conventional enterprise. The factor of innovation capacity is also taken into account when assessing the development value of a company [10]. Profitability reflects an enterprise's ability to earn profits in the market. Risk resistance reflects an enterprise's ability to resist crises in the process of market competition; the stronger its ability, the less likely it is to be affected by market risks, and the more stable its operations. Management capability reflects an enterprise's management level of its operations; the stronger its ability, the more reasonably it can allocate its resources. Innovation capability reflects the ability of the enterprise to innovate technology.

## 2.2 Prediction algorithm based on optimized BPNN

After constructing the factors and indicators for evaluating the development value of technology-based SMEs, the corresponding data can be collected to assess the development value of the enterprises. The traditional evaluation method is to collect the corresponding data according to the framework constructed in Figure 1 and then manually assign the weights to the indicators for aggregation calculation; however, manual calculation is inefficient, and assigning the weights manually is strongly subjective [11].

As a deep learning algorithm, a BPNN algorithm requires training samples to train the weight parameters within the hidden layer before it can be used formally. During the training of a BPNN algorithm, forward calculation is performed on the input data, the obtained results are compared with the expected outcomes in the training sample labels at the output layer, and the weight parameters in the hidden layer are adjusted in a reverse manner based on their discrepancy. The above-mentioned traditional BPNN algorithm modifies the weight parameters reversely based on the error during training, but the adjustment process requires a suitable learning step length. If the step length is too small, the BPNN algorithm will converge slowly; if it is too large, the BPNN algorithm will fluctuate around the optimal solution and fail to converge. In order to improve this defect, this paper introduces a particle swarm algorithm (PSO) to optimize the BPNN [12].

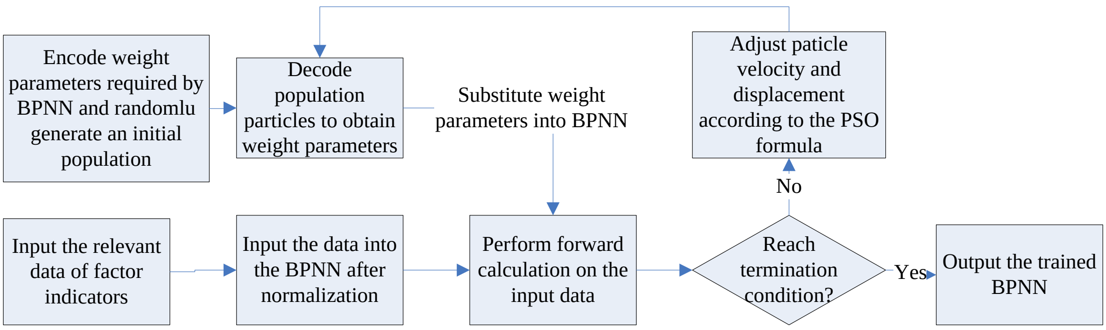


Figure 2: BPNN training process after PSO optimization

The PSO improves the traditional BPNN algorithm by adjusting and optimizing the particles in the PSO population, i.e., it changes the training method of the traditional BPNN. The training steps are shown in Figure 2.

① The weight parameters the BPNN algorithm requires are encoded to randomly generate a random population. The weight parameter scheme for the BPNN is represented by the coordinates of each particle in the population [13].

② The weight parameters are obtained by decoding the population particles. The coordinates of the particle in the search space are the particle's weight parameter scheme. The search space's axis count is determined by the quantity of weight parameters that require optimization within the BPNN algorithm. Every axis represents a range of values for a weight parameter. The decoded weight parameters are substituted into the BPNN algorithm.

③ The relevant data of the factor indicators are input and normalized to reduce the interference caused by the different dimensions. The normalization formula is:

$$x'_{ij} = \frac{x_{ij} - x_{i,\min}}{x_{i,\max} - x_{i,\min}}, (1)$$

where $x'_{ij}$ is the $j$-th data in the $i$-th category of indicator after normalization, $x_{i,\max}$ and $x_{i,\min}$ are the maximum and minimum values among the $i$-th category of indicator before normalization, and $x_{ij}$ is the $j$-th data in the $i$-th category of indicator before normalization.

④ Forward calculation is carried out on the input data in the hidden layer within the BPNN algorithm:

$$a = f\left(\sum_{i=1}^{n} \omega x_i - \beta\right), (2)$$

where $a$ is the result produced by each individual layer, $\beta$ is the adjustment term of every layer, $f(\bullet)$ is the activation function, and $\omega$ is the weight between layers.

⑤ The determination of whether the termination condition for the entire training is reached is made after obtaining the calculation result by the output layer. If it reaches the termination condition, the trained BPNN algorithm is output; if not, it returns to step ⑥. The termination criterion is met when either the maximum number of training iterations is reached or the difference between the calculated outcome and the expected outcome fails to converge within the predetermined threshold range.

⑥ The population particles are iterated over by the adjustment formula of PSO [14]:

$$\begin{cases} v_i(t+1)=\varpi v_i(t)+c_1r_1(P_i(t)-x_i(t))+c_2r_2(G_g(t)-x_i(t)) \\ x_i(t+1)=x_i(t)+v_i(t+1) \end{cases}, \quad (3)$$

where $v_i(t+1)$ and $x_i(t+1)$ are particle $i$ 's velocity and position following a single iteration, $v_i(t)$ and $x_i(t)$ are particle $i$ ' velocity and position prior to the iteration, $\varpi$ is the inertia weight of the particle, $c_1$ and $c_2$ are learning factors, $r_1$ and $r_2$ are random values ranging from 0 to 1, $P_i(t)$ is the historical optimal position experienced by particle $i$ , and $G_g(t)$ is the global optimal position. After iterating over the population particles according to equation (3), it returns to step ②.

The BPNN algorithm is trained repeatedly according to the above steps until the termination condition is met. When the trained BPNN algorithm is used, the evaluation result of enterprise development value can be obtained by inputting the indicator data into the BPNN algorithm for forward calculation.

# 3 Simulation experiments

## 3.1 Experimental data

The laboratory server was utilized to conduct the simulation experiment. The sample data required for the simulation experiment were obtained from enterprises registered in the growth enterprise market (GEM) located in Sichuan Province. The reason for selecting the listed enterprises from GEM is that the listed enterprises release their financial reports every year and it is easier to obtain the indicator data of the sample. The reason for choosing GEM is that the listed enterprises in GEM will be in a state of development for a long period, and their financial reports are more suitable for the simulation experiment.

After excluding the fragmented data and the financial report data of non-technology enterprises, 100 groups of data related to technology-based SMEs were selected. Every group of data contained the financial report data of the corresponding enterprises from 2017 to 2019. To reduce the impact of data fluctuations, the average value of the financial report data in the three years was used as the indicator data of the enterprise samples. Seventy sample data groups were chosen at random for training purposes, while the remaining 30 groups were designated as test samples.

In addition to the data of 18 indicators under the four major influencing factors described above, the corresponding numerical labels showing the development value of the enterprises were also needed in the simulation experiment. The development value of 100 technology-based SMEs was rated between 0 and 1 by ten experts and the analytic hierarchy process method.

## 3.2 Experimental setup

The input layer of the PSO-BPNN algorithm was configured with 18 nodes, while the output layer consisted of a single node. The activation function in the hidden layer adopted the commonly used sigmoid, which is more closely aligned with nonlinear patterns. The number of hidden layers and nodes per layer was determined through orthogonal experiments. The number of hidden layers was set to 1, 2, and 3, respectively, while the number of nodes per layer was set to 6, 7, 8, 9, and 10. The performance under different numbers of hidden layers and different numbers of hidden layer nodes was tested, and the results were presented in Table 2. Based on the results of orthogonal testing, the number of hidden layers was set to 2, and the number of hidden layer nodes was set to 8. After referring to a literature [15], the PSO part used for training was configured with the following parameters: a population size of 20, learning factors set to 1.5 each, an inertia weight of 0.8, and a maximum limit of 1,000 training sessions.

Table 2: The predictive error of the PSO-BPNN algorithm under different numbers of hidden layers and nodes

| Number of hidden layer nodes | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|
| One hidden layer | 3.8% | 2.9% | 2.3% | 2.8% | 3.9% |
| Two hidden layers | 2.6% | 1.5% | 1.1% | 1.6% | 2.3% |
| Three hidden layers | 3.7% | 2.8% | 2.5% | 2.9% | 3.8% |

To assess the value of enterprise development, the effectiveness of the PSO-BPNN algorithm was evaluated by comparing it with traditional algorithms such as BPNN and ELM. The parameters of the BPNN in the conventional BPNN algorithm were identical to those used in the PSO-BPNN algorithm [16]; the learning rate was set as 0.02, and the maximum training number was 1000 times.

The parameters associated with the ELM algorithm were set as follows. The input layer consisted of 18 nodes, while the hidden layer comprised 17 nodes. The output layer was composed of a single node. A sigmoid function served as the activation function.

Comparing the ELM, traditional BPNN, and PSO-BPNN algorithms can only preliminarily verify the precision of the PSO-BPNN algorithm in calculating the development value, but it does not directly reflect whether the development value data calculated by this algorithm really measures the development ability of the enterprise. Thus, this paper conducted correlation analyses on the average market value growth rate of the enterprise and the calculated development value data from 2017 to 2019 using SPSS software. The significance level of the correlation was measured by the P-value test method. A P value less than 0.05 meant that the correlation was significant.

## 3.3 Experimental results

Since the ELM algorithm used for the comparison uses the generalized inverse matrix to directly calculate the weight parameters of the hidden layer without repeated iterative calculations, only BPNN and PSO-BPNN algorithms were compared, as presented in Figure 3. It was observed from Figure 3 that both algorithms converged to stability in the training process, but the comparison of the two convergence curves showed that the PSO-BPNN algorithm converged to stability more quickly than the traditional BPNN algorithm and had a smaller mean square error (MSE) when converging to stability.

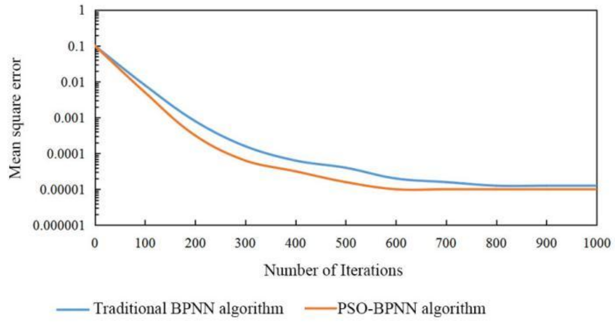


Figure 3: Convergence curves of the conventional BPNN and PSO-BPNN algorithms during the training process

The errors of the ELM, traditional BPNN, and PSO-BPNN algorithms were tested by the test set after training by the training set, and their evaluation errors of enterprise development value are presented in Figure 4. It was observed from Figure 4 that the evaluation error of the ELM algorithm fluctuated severely (3.00%-4.50%) on different test samples and had the largest error; the evaluation error of the traditional BPNN algorithm on different test samples had less fluctuations than the ELM algorithm (1.50%-2.50%), and its evaluation error was smaller than the ELM algorithm; the evaluation error of the PSO-BPNN algorithm on different test samples fluctuated the least, ranging from 1.00% to 1.25%, and the overall evaluation error was the smallest.

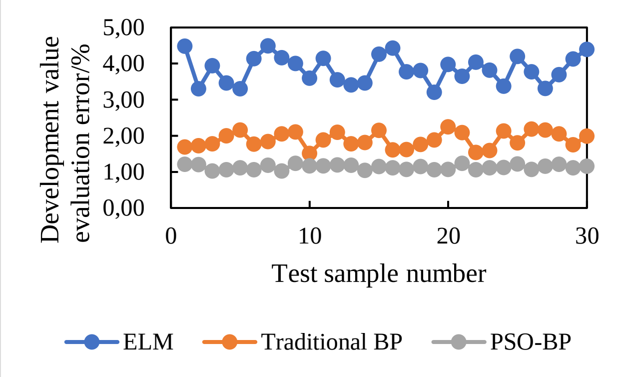


Figure 4: Evaluation errors of the three-enterprise development value evaluation algorithms for the test samples

The above comparison of the test errors between the three-enterprise development value evaluation algorithms only initially verified that the PSO-BPNN algorithm could predict the development value more accurately, but it did not show that the calculated development value assessment number could reflect the real development level of the enterprise. Thus, the average market value growth rate from 2017 to 2019 was taken as the actual embodiment of the enterprise development value, and its correlation with the calculated development value assessment number was analyzed. The findings are presented in Table 3. The correlation coefficient between the development value assessment number and the market value growth rate was 0.397, and the P value was 0.002, indicating a statistical significance, i.e., the correlation between the development value assessment number and the market value growth rate was significant. The correlation analysis results showed that the development value assessment number calculated by the PSO-BPNN algorithm could effectively reflect the development value of the enterprise, and the assessment model was feasible.

Table 3: Results of the correlation analysis between the enterprise development value calculated by the PSO-BPNN algorithm and the market value growth rate

| | Development value assessment number | Market value growth rate |
|---|---|---|
| Development value assessment number | 1.000 | 0.397 |
| Market value growth rate | 0.397 | 1.000 |
| P value | 0.002 | 0.002 |

# 4 Discussion

In the rapidly changing technological environment, accurately forecasting the development value of technology-based enterprises is crucial for investors, managers, and policymakers. Traditional forecasting methods often rely on experience or simple linear models, which struggle to capture the complexity and dynamics of technology-driven enterprises. With the advancement of artificial intelligence technology, neural networks have become widely used as powerful nonlinear modeling tools in the field of prediction. Among them, the BPNN algorithm is an ideal choice for forecasting the development value of technology-based enterprises due to its simple structure, ease of implementation, and strong self-learning ability. However, the traditional BPNN algorithm suffers from issues such as slow convergence speed during training and a tendency to get stuck in local optima. Therefore, this article introduced PSO to optimize the BPNN algorithm. BPNN parameter schemes were represented by particles, and the particle swarm was iterated using PSO to replace the traditional training method. In the subsequent simulation experiments, the convergence curves of the traditional and improved BPNN algorithms during training were compared, and the prediction errors were also compared between the ELM, traditional BPNN, and improved BPNN algorithms. Finally, the predicted results of the improved BPNN algorithm were used to analyze the correlation between enterprise development value and the growth rate of enterprise market values.

It was found from the comparison of the convergence curves between the traditional and improved BPNN algorithms that the improved algorithm converged faster and had a smaller training error when it reached stability. The comparison of the results of the ELM, traditional BPNN, and improved BPNN algorithms showed that the improved algorithm had the smallest prediction error. The reason for these results lies in using particle swarm iteration instead of traditional back-propagation error-based parameter adjustment during training in the PSO-improved BPNN algorithm. When utilizing PSO to obtain suitable parameters for the BPNN algorithm, multiple particles in the swarm were involved, avoiding the drawback of single-directional adjustment in the traditional back-propagation error-based parameter adjustment method and minimizing the possibility of falling into local optima.

The novelty of this article lies in the use of the PSO algorithm to replace the back-propagation error-based parameter adjustment method in the traditional BPNN algorithm, thereby avoiding local optima as much as possible and providing an effective reference for accurately predicting the development value of enterprises.

# 5 Conclusion

This paper briefly introduces the technology-based SMEs and the factors affecting their development values. Then, the BPNN algorithm was chosen to evaluate the development value of enterprises. After optimizing the BPNN algorithm by the PSO, the PSO-BPNN algorithm was simulated and compared with the ELM and traditional BPNN algorithms. The results are as follows. In the training phase, the ELM algorithm used a generalized inverse matrix to calculate the weight parameters without repeated iterations directly, and the MSE of the traditional BPNN and PSO-BPNN algorithms gradually converged to stable in the process of training iterations, among which the PSO-BPNN algorithm converged faster and had smaller MSE after converging to stability. In the test by the test samples, the computational error of the ELM algorithm fluctuated from 3.00% to 4.50%, the error of the conventional BPNN algorithm fluctuated from 1.50% to 2.50%, and the error of the PSO-BPNN algorithm fluctuated from 1.00% to 1.25%. There was a significant correlation between the enterprise development value assessment value calculated by the PSO-BPNN algorithm and the market value growth rate, and the PSO-BPNN algorithm could effectively make an assessment of the enterprise development value.

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