The evaluation of marketing competitiveness of B2B E-commerce enterprises based on optimized deep learning networks

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Abstract. In the context of e-commerce trade between enterprises, there are problems such as price wars, false advertising, and unreasonable operations aimed at seizing market share. However, traditional estimation methods cannot provide a reasonable evaluation of the marketing competitiveness of e-commerce enterprises from an overall perspective. To help enterprises better clarify their own position and quantify their marketing competitiveness, a competitiveness evaluation model based on optimized deep learning networks is proposed. By combining subjective and objective evaluation methods, the indicators that affect the marketing competitiveness of enterprises are assigned to obtain the final competitiveness value. The research outcomes expressed that the max absolute error of the model constructed by the research institute was 0.0006, the max relative error was 0.0045, and the model accuracy was 99.85%. In the secondary indicator experiment of marketing competition, the model determined that the turnover rate of fixed assets had the greatest impact, with a weight value of 0.1263. Nine companies were randomly selected for market value estimation, and the average relative error of the model was 14.90%, which was lower than the mean relative error of the relative valuation, cash flow and absolute valuation methods, with numerical differences of 8.03%, 2.94%, and 0.12%, respectively. The research findings illustrated that the model constructed by the research institute had good performance and certain reference values for evaluating the marketing competitiveness of e-commerce enterprises.

Keywords: Marketing competitiveness / backpropagation neural network / E-commerce enterprises / absolute valuation method / combination weight coefficient method

1 Introduction

As the growth of internet technology, the number of people conducting online transactions has also increased, and the era of Business-to-Business (B2B) e-commerce has also emerged. B2B achieves fast and effective business transactions between enterprises through the exchange and transmission of data information. It enables the internal network and corresponding product services to establish connections with customers through websites or clients, which can achieve the goal of rapid supply and sales, better serving customers, and ensuring the development of its own enterprise business [1]. The development of B2B e-commerce has gone through three eras to this day. During the B2B e-commerce 1.0 era, E-Commerce Companies (ECC) tended to prefer the public use of data information and completed corresponding transactions by charging service fees for online information. It can be said that during the 1.0 era, they mainly engaged in information trade. The use of cloud computing and big data in the 2.0 era makes companies and supply chains more dependent on the e-commerce model. Through the calculation and push of big data, enterprises can more accurately understand consumer preferences, so as to establish faster supply chain services [2]. Although the development of B2B e-commerce has to some extent promoted the growth of China’s economic power, the price war, false advertising and unreasonable operation caused by malicious competition among B2B ECC have seriously disrupted market orders and undermined consumer trust and satisfaction. Evaluating the marketing competitiveness of enterprises can help ECC better understand their own positioning and formulate relevant measures to ensure their survival and development, thus promoting the healthy development of the entire ECC. However, some commonly used estimation methods are difficult to adapt to the evaluation of overall e-commerce marketing competitiveness. To address the above issues, a backpropagation (BP) model is proposed to optimize deep learning networks (DLN) to
estimate the marketing competitiveness of B2B ECC. The first chapter of the study summarizes and narrates the relevant works in recent years. The second chapter constructs a BP model for evaluating the competitiveness of enterprise marketing. The third chapter verifies the effectiveness of the model built by the research institute and obtains experimental results. The fourth chapter summarizes the research results and draws research conclusions.

2 Related words

The techniques and theories related to backpropagation neural networks (BPNNs) have been widely utilized. Mingkang et al. conveniently used BPNNs to predict the residual displacement of bilinear single level of freedom systems [3]. Hu et al. combined a genetic algorithm and BP to build a new prediction model for solar ultra-short-term radiation, and tested the constructed model in practical situations [4]. Zeng et al. proposed a forensic Weibo lubricating oil detection scheme assisted by BPNNs, and verified the effectiveness of their proposed scheme through experiments [5]. Shi Lai et al. proposed a method to model the relation between slag composition and boron content by a BP to study the residual results of boron in the slag refining, and verified the performance of the model through experiments [6]. Zhang et al. proposed an improved genetic algorithm-based BPNN model to predict hydrogen damage in corroded pipelines. The performance of the model was verified through experiments [7]. To address the bad prediction accuracy and poor convergence performance of the conventional urban construction land model, Li et al. proposed a prediction model for the speed of sustainable city construction land based on BP. Experiments proved that the proposed model had good convergence and high accuracy [8]. Jinlong et al. raised an evaluation model based on BP to forecast the ultra-high cycle fatigue life of centrifugal impellers. By combining influencing factors with the model, they predicted the internal inclusions and bright surface areas of particles [9]. Zhang B et al. proposed a single-pass high-precision BP model with color stripe projection profilometry to lessen the impact of nonlinear factors. The performance of the model was verified through experiments [10]. Carlos et al. proposed a particle swarm optimization to study the characteristic variables that determine the resonant frequency of the transducer and proved that the algorithm had strong robustness and high efficiency through experiments [11]. In marketing competitiveness, Carlos M et al. used the partial least squares method to analyze the marketing and innovation capabilities of small timber enterprises in Misiones to promote market employment in poor countries. Combined with experiments, they obtained the impact of trust on the marketing and innovation ability of enterprises [12]. To effectively evaluate the competitiveness of enterprises, Li et al. combined factor analysis and other methods to construct a data attribute reduction model, and conducted relevant evaluation work through multi-attribute fuzzy decision-making evaluation. After verification, the application effect of this method is good [13]. To raise the integrated assessment impact of the competitiveness of the enterprise, Liu proposed a structural equation logistics enterprise competitiveness comprehensive evaluation model and analyzed its real competitiveness and growth potential through experiments [14].

In summary, the performance of BPNNs was stable and widely used, but there was little research on their marketing competitiveness. Based on this, the study proposed a model based on a BPNN with BP optimization, which combined the combination weight coefficient method to assess the marketing competitiveness of B2B ECC.

3 Construction of an evaluation model for the marketing competitiveness of B2B ECC based on optimized DLN

This study uses a BPNN combined with a combination weight method to quantify the factors that affect the marketing competitiveness of enterprises. The constructed influencing factor indicators are given different weights based on the degree of influence, and finally, the marketing competitiveness of ECC is output.

3.1 Model construction based on BP

The B2B e-commerce transaction model has become the largest transaction model in China, and merchants complete corresponding business transactions through Internet technology or other business network platforms. The goal of the B2B e-commerce model is to ensure that a company generates revenue while stabilizing its online operating profits. Like conventional offline trade, B2B e-commerce includes three elements: buying and selling, cooperation, and service. Its business evolution characteristics are shown in Figure 1.

From Figure 1, the relationship between the number of buyers and sellers in the B2B e-commerce model has been constantly changing, with the market evolving from a “buyer’s market” to a “seller’s market”. Finally, in the B2B business model, the number of buyers and sellers reaches a 1:1 balance. With the popularization of internet technology, the number of e-commerce is increasing, which has led to many micro and small companies losing their ability to survive and adapt to the current trade environment. At the same time, some companies that are transitioning to online internet operations may also face difficulties due to a lack of business strategy. Traditional e-commerce tools include websites, blogs, social media, copywriting, marketing emails, and more. However, the designated business strategies under these business tools may result in unclear customer attractiveness, neglect of additional factors, financial and actual estimation errors, and other issues. To better assess the marketing competitiveness of B2B ECC, research has introduced optimized DLN to construct corresponding evaluation models. As a general term of pattern analysis method, deep learning (DL) is mainly divided into three types: convolutional neural network, multi-layer neuron self-coding neural network and deep confidence network. BP has
good classification capability and multi-dimensional function mapping ability and can solve the XOR problem that simple perceptron cannot solve, so it is widely used. The structure of the BP is expressed in Figure 2.

From Figure 2, the basic mechanism of BP includes three parts: the output, hidden and output layers. The main function of the input layer is to input relevant data. The hidden layer mainly involves the analysis and processing of input and output data. The connection between the input and output layers is established through data processing methods such as weight, deviation value and activation function, and the final result is output by the output layer. The energy of nodes between each layer is not transmitted from the medium where it is located to the adjacent medium, meaning that the nodes between each layer are not coupled. The n-layer nodes only have an effect on the n + 1 layer nodes, and the activation of nodes involves the Sigmoid function. The relevant function is shown in formula (1).

\[ P(y = j) = \frac{e^{x^T W_j}}{\sum_{k=1}^{K} e^{x^T W_k}}. \]  

In formula (1), \( P(y = j) \) indicates the probability that the sample \( x \) belongs to the \( j \)th classification. \( k \) means the result of a linear function. \( W \) denotes the weight value. To ensure the accuracy of the output results, the BP also uses forward and backward propagation methods to correct the output results. The forward propagation mainly involves the neurons in the input layer receiving external information, transmitting it to the neurons in the middle-hidden layer, and then the neurons in the hidden layer process and transform the information. One or multiple hidden layers are set according to relevant requirements. BP mainly involves situations where the error between the actual output and the ideal output exceeds the expected value. Starting from the output layer, the weights of each layer are corrected using an error gradient descent method, and in the order of the hidden and input layers, the weight values of each layer are continuously adjusted through continuous forward and backward propagation. Finally, the learning and training of the entire neural network is completed. When the output error reaches the expected level or reaches the predetermined number of learning iterations, the BPNN completes training and ends learning. The BPNN model has a unique learning principle, using the error BP mechanism to constantly adjust the weights, and finally minimize the error. The error of the neural network refers to the difference between the desired output and the output of the network.
3.2 Model construction of competitiveness evaluation

Indicators for ECC based on improved BPNN

For e-commerce trade, constructing a corresponding evaluation model for marketing competitiveness first requires determining the factors that affect the marketing competitiveness of B2B ECC. With relevant data, the factors that have a significant effect on e-commerce trade marketing include resources, performance, growth, and technological innovation. The corresponding impacts of these four factors are shown in Figure 3 [15].

From Figure 3, the evaluation indicators for the marketing competitiveness of B2B ECC involve enterprise scale, operation, and management. Therefore, clear evaluation values must be established for each evaluation indicator, reflecting the advantages and disadvantages of each comparative evaluation indicator, to better serve ECC and contribute corresponding theoretical references to improving the marketing competitiveness of enterprises. It integrates business influencing factors with BPNN [16,17]. Using Matlab neural network toolbox to develop a program, a B2B ECC marketing competitiveness evaluation model based on BP is drawn, as expressed in Figure 4 [18]. Using the BP model combined with combined weights, the evaluation index weights constructed under the four influencing factors of resources, performance, growth, and technological innovation are calculated. The corresponding marketing competitiveness values of B2B ECC are obtained by comparing the standardized data. The expected value of the training sample is the weighted sum value of ECC.

From Figure 4, when evaluating the marketing competitiveness of ECC, it needs to first determine the evaluation indicators, collect the number of samples, and then establish the BP. As a type of artificial neural network, BPNN helps the neural network learn input data and adjusts the weights of the neural network through learning. Compared to artificial neural networks, the research method is based on the BPNN and improved through the Levenberg Marquardt (LM) algorithm, which improves the performance of the algorithm and avoids local extremum situations. In the initialization stage of the network, the learning of the BP can be divided into input, hidden and output layers learning. The corresponding number of nodes is represented as $N$, $M$, $K$, and the output signal of $m$ training samples is $x_i$, and the output signal is $y_i$. The unit input signals of $n$ outputs on $j$ neural units are shown in formula (2).

$$O_j = f\left(\sum_{i=1}^{n} x_i w_{ij} - \theta_j\right).$$

In formula (2), $w_{ij}$ means the weight coefficient. $\theta_j$ indicates the threshold of the neural unit $j$. $x_i$ means the weighted input of the neuron. The unit input signal is
weighted by the sigmoid function to obtain formula (3).

\[ O_j^p = \frac{1}{1 + \exp\left(\sum_{i=1}^{n} x_{ij}w_{ij} - \theta_j \right)} \]  

The output of the current layer is utilized as the input value of the next layer, which is propagated forward through the hidden layer to the output layer. Then, the obtained value is contrast to the expected value to obtain the unit error between the expected and the output value. The unit error is expressed as \( E_i \), and its function is expressed in formula (4).

\[ E_i = \frac{1}{2} \sum_{k=1}^{k} (y_{ik} - y_k)^2. \]  

In formula (4), \( y_{ik} \) and \( y_k \) denotes the expected and the actual output of the neuron \( k \) on the output layer. From this, the total error of \( m \) training samples can be summarized, as shown in formula (5).

\[ E = \frac{1}{m} \sum_{i=1}^{m} E_i. \]  

By calculating the recursive process layer by layer and adjusting the weights to reduce the error value, the formula involved in BPNN weight correction is shown in formula (6).

\[ e_k(p) = y_{ik}(p) - y_k(p). \]  

In formula (6), \( e_k(p) \) infers to the error signal of the neuron \( k \) during the \( p \)th iteration. \( y_{ik}(p) \) denotes the expected value during the \( p \)th iteration. \( y_k(p) \) indicates the output value during the \( p \)th iteration. Based on \( e_k(p) \), it is used to adjust the connection weight for the \( p + 1 \) iteration. The relevant functional expressions are shown in formula (7).

\[ w_{jk}(p + 1) = w_{jk}(p) + \Delta w_{jk}(p). \]  

In formula (7), \( w_{jk}(p + 1) \) denotes the connection weight between neuron \( j \) and neuron \( k \) at \( (p + 1) \)th, and \( \Delta w_{jk}(p) \) indicates the weight adjusted during \( p + 1 \) iteration. The adjusted weight calculation formula is shown in (8).

\[ \Delta w_{jk}(p) = \alpha \cdot y_j(p) \cdot \beta_k(p). \]  

In formula (8), \( \alpha \) means the learning rate. The value range is \([0, 1]\). \( y_j(p) \) denotes the output value of neuron \( j \). \( \beta_k(p) \) denotes the error gradient of neuron \( k \). The error gradient calculation formula for neuron \( k \) is shown in formula (9).

\[ \beta_k(p) = \frac{\partial y_k(p)}{\partial x_k(p)} \cdot e_k(p). \]  

In formula (9), \( x_k(p) \) indicates the weighted input of neuron \( k \). \( e_k(p) \) refers to the error of neuron \( k \). If the neuron \( k \) is located in the input layer, its error calculation is formula (10).

\[ e_k(p) = e_k(p). \]  

If neuron \( k \) is in the hidden layer, its error calculation is formula (11).

\[ e_k(p) = \sum_{i=1}^{l}(e_i(p) \cdot w_{ki}(P)). \]  

In formula (11), \( l \) stands for the number of neurons in the output layer. \( w_{ki}(P) \) refers to the connection weight between neuron \( k \) and neuron \( i \). If the neuron \( k \) is in the output layer, its error calculation is formula (12).

\[ e_k(p) = y_k(p) \cdot [1 - y_k(p)] \cdot e_k(p). \]

The number of input layer nodes is set according to the evaluation indicators for marketing competitiveness of B2B ECC. Based on the number of secondary indicators, the number of output layer nodes is positioned at 16. The
final competitiveness value is output through the evaluation model constructed by the research institute. Considering that the training function of the model needs to be chosen with the indicators of B2B business marketing competitiveness and the characteristics of business data training samples, while the training function can repeatedly adjust the network weights and thresholds to reduce the value of the network performance function, which meets the learning requirements proposed by the research institute, the training function is selected to train the constructed model. Overall, the study uses a three-layer BPNN containing 1 hidden layer. The number of nodes in the output layer is 1, which is the competitive output value of B2B ECC. The activation function is present in each neuron of the model and is used to process the data. After data processing, each output data is combined with the corresponding weight, and this new value is input to the next processing neuron in the next layer, until the last output neuron. After the input layer is standardized in [0,1], it meets the value domain requirements of the log-sigmoidal type function mapping. So, the selected function from the input layer to the hidden layer is the logarithmic sigmoidal type function, and the function from the hidden layer to the output layer uses the purelin type function. In the standardization processing of sample data, maxmin function is used to standardize the original data, so that the original data is converted into (0,1) type function. In the standardization processing of sample data, the logarithmic sigmoidal type function, and the function selected from the input layer to the hidden layer is the elements of the log-sigmoidal type function mapping. So, the standardized in [0,1], it meets the value domain requirement. The input value of B2B ECC is obtained through training and testing samples, while the training error was determined by the model. It listed the names of 23 companies and indicated their corresponding codes, as shown in Table 1. It selected the annual report and relevant statistical data of commercial companies were numerous and different, with a total of 23 listed companies. The maxmin function was used to standardize the collected raw data. The partial results of data standardization still could not reflect the impact between learning outcomes and learning errors is shown in Figure 5.

4 Result analysis of the evaluation model for marketing competitiveness of B2B business enterprises

It selected the annual report and relevant statistical data of B2B ECC in 2016. The selection of listed companies followed the principles of balanced and stratified sampling, and required a reasonable amount of training sample data for ECC to be collected. It randomly selected 20 companies to train and construct a neural network based on standardized data. Three companies were utilized as the test set for the model, with a target accuracy of 10-5500 training times. It compared the training results of the number of hidden nodes in each layer, and selected the number of nodes in the hidden layer with the smallest learning error as the final number of hidden layers. The impact between learning outcomes and learning errors is shown in Figure 5.

In Figure 5a, the training error of the algorithm varied under different learning rates. When the learning rate was between 0.1 and 0.3, the training error was 0, and when the learning rate was 0.4, the training error was maximum. In Figure 5b, the MSE value of the algorithm varied with different Epochs values. When the Epochs value varied between 0.1 and 0.3, the training error was 0, and when the learning rate was 0.4, the training error was maximum. In the experiment, it was found that the training of the learning model using the 0.003 learning rate in the default Matlab program would show a slower rate of convergence, so the learning rate was determined as 0.1. It listed the names of 23 companies and indicated their corresponding codes, as shown in Table 1.

In Table 1, the corresponding codes for different listed companies were different, with a total of 23 listed companies. The maxmin function was used to standardize the collected raw data. The partial results of data processing for 23 listed companies are displayed in Table 2.

Table 2, for different companies under the same competition index, the value of the total sales of A1 company was 0.1612,0.1589 smaller than A2 company, which was 0.0023. The value of the total sales of A7 company was 0.2945. From Table 2, the competition indicators of B2B commercial companies were numerous and finely classified, and the results of data standardization still could not reflect the marketing competitiveness of the enterprise. Therefore, the study calculated the weights of each evaluation indicator through the combination of the BP model and weights, and compared the standardized data to gain the corresponding marketing competitiveness value of B2B ECC. The combined weight results are shown in Table 3.

\[
E(x) = \frac{1}{2} \sum_{i=1}^{n} [d(i) - y(i)]^2. \tag{13}
\]

In formula (13), \( d \) represents the expected input vector, \( y \) represents the actual output vector, and the target error is set to \( e(x) \). It sets the weight and threshold vector of the \( k \) iteration to \( x^k \), and \( \Delta x \) is the change in weight and threshold, then the new weight and threshold vector is \( x^{(k+1)} \). For the Newton algorithm, \( \Delta x = -[\nabla^2 E(x)]^{-1} \cdot \nabla E(x), \) \( \nabla E(x) \) represent gradients, and \( \nabla^2 E(x) \) represent the Hessian matrix of \( E(x) \). To make the Hessian matrices reversible, an approximate calculation is required for \( \nabla^2 E(x) \). \( S(x) = \sum_{i=1}^{n} e_i(x) \cdot \nabla^2 e_i(x), \)

When approaching the extreme point, \( S(x) \approx 0 \), revised to Gaussian Newton method, \( \Delta x = -[J^T(x) \cdot J(x)]^{-1} \cdot J(x) \cdot E(x), \) \( J(x) \) is the Jacobian matrix. The LM algorithm also improves the Gaussian Newton method, and after the improvement, \( \Delta x = -[J^T(x) \cdot J(x) + \mu \cdot I]^{-1} \cdot J(x) \cdot E(x), \) \( \mu \) represents the adjustment coefficient, and \( I \) is the identity matrix. When \( \mu = 0 \), the LM algorithm is the Gaussian Newton method. When the value of \( \mu \) is large, the LM algorithm approaches the gradient descent method.
From Table 3, among the secondary indicator weights, the fixed asset turnover rate had the highest weight value of 0.1263. The second was brand value with a weight value of 0.1152, and the third was the proportion of R&D investment to total sales with a weight value of 0.1035. The weight values of other marketing competitiveness indicators were all below 0.10. By combining the combination weight table and processing the standardized sample data through weighted summation, the gap between the expected and actual marketing competitiveness values of 10 randomly selected B2B ECC was obtained. The experimental outcomes are expressed in Figure 6.

Table 1. Selected company names and their corresponding abbreviations.

<table>
<thead>
<tr>
<th>Enterprise</th>
<th>Substitution</th>
<th>Enterprise</th>
<th>Substitution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Focus Technology</td>
<td>A1</td>
<td>Deep Seg</td>
<td>A13</td>
</tr>
<tr>
<td>Shanghai Ganglian</td>
<td>A2</td>
<td>Longping High Tech</td>
<td>A14</td>
</tr>
<tr>
<td>Business Treasure</td>
<td>A3</td>
<td>Dongfang Group</td>
<td>A15</td>
</tr>
<tr>
<td>Small Commodity City</td>
<td>A4</td>
<td>Netstay Technology</td>
<td>A16</td>
</tr>
<tr>
<td>Zhejiang Dongfang</td>
<td>A5</td>
<td>Ortega</td>
<td>A17</td>
</tr>
<tr>
<td>Hikvision</td>
<td>A6</td>
<td>Zhejiang University Network New</td>
<td>A18</td>
</tr>
<tr>
<td>Smart Energy</td>
<td>A7</td>
<td>Baoxin Software</td>
<td>A19</td>
</tr>
<tr>
<td>Zhongye Da</td>
<td>A8</td>
<td>Changjiang Investment</td>
<td>A20</td>
</tr>
<tr>
<td>Ruimaotong</td>
<td>A9</td>
<td>Development of outward transportation</td>
<td>A21</td>
</tr>
<tr>
<td>Tengbang International</td>
<td>A10</td>
<td>Haihong Holdings</td>
<td>A22</td>
</tr>
<tr>
<td>Zheshang Zhongtuo</td>
<td>A11</td>
<td>Shenzhen Huaqiang</td>
<td>A23</td>
</tr>
<tr>
<td>Agricultural products</td>
<td>A12</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2. Partial results of standardized data collection from 23 listed companies.

<table>
<thead>
<tr>
<th>Evaluating indicator</th>
<th>Total number of employees in the enterprise</th>
<th>Total sales</th>
<th>Net operating profit margin</th>
<th>Return on total assets</th>
<th>Net return on assets</th>
<th>Year-on-year growth rate of total operating revenue</th>
<th>Current ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>0.0844</td>
<td>0.1612</td>
<td>0.5771</td>
<td>0.1933</td>
<td>0.1215</td>
<td>0.3218</td>
<td>0.2881</td>
</tr>
<tr>
<td>A2</td>
<td>0.0681</td>
<td>1.0012</td>
<td>0.0</td>
<td>0.0023</td>
<td>0.1162</td>
<td>0.5954</td>
<td>0.0533</td>
</tr>
<tr>
<td>A3</td>
<td>0.0288</td>
<td>0.0023</td>
<td>0.1312</td>
<td>0.0442</td>
<td>0.0108</td>
<td>0.5516</td>
<td>0.5254</td>
</tr>
<tr>
<td>A4</td>
<td>0.2245</td>
<td>0.1663</td>
<td>0.5354</td>
<td>0.1596</td>
<td>0.2477</td>
<td>0.2456</td>
<td>0.0268</td>
</tr>
<tr>
<td>A5</td>
<td>0.0315</td>
<td>0.1042</td>
<td>0.5477</td>
<td>0.2633</td>
<td>0.3277</td>
<td>0.0520</td>
<td>0.0580</td>
</tr>
<tr>
<td>A6</td>
<td>1.0002</td>
<td>0.7713</td>
<td>0.8245</td>
<td>1.0032</td>
<td>1.0014</td>
<td>0.2599</td>
<td>0.1887</td>
</tr>
<tr>
<td>A7</td>
<td>0.4644</td>
<td>0.2945</td>
<td>0.0855</td>
<td>0.0793</td>
<td>0.1212</td>
<td>0.1496</td>
<td>0.0853</td>
</tr>
</tbody>
</table>
From Figure 6, the expected value curve of the enterprise obtained from the BP model constructed by the research institute could fit the actual curve well, and the model accuracy could reach 99.85%. Among them, Wangsu Science & Technology A16 had the highest expectation, 0.4241. Combining the company’s business content, Internet content distribution and acceleration, cloud computing and security, etc., it was in line with the actual situation. The second and third expected values were Small Commodity City A4 and Eastern Bloc A5, respectively. The expected values were 0.2472 and 0.2464. The other three companies with expected values above 0.20 were Longping Technology 0.2095, Shanghai Ganglian 0.2079 and Focus Technology 0.2036, respectively. To further investigate the accuracy of the model, three companies from different industries were randomly selected to compare the difference between expected and measured values. The research findings are displayed in Figure 7.

From Figure 7, the models constructed by the research institute had good detection results for the corresponding industries of the three companies tested, namely Internet information, agricultural product management, and the IT service industry. Among them, the models had the smallest ARE in predicting the marketing competitiveness of the business treasure enterprise, with 0.0001 and 0.0006, respectively. The BP model had the highest ARE in predicting agricultural product enterprises, with values of 0.0006 and 0.0045, respectively. From the output results, the absolute valuation (AV) method and relative valuation (RV) method errors between the estimated values and expectations of the enterprise marketing competitiveness model constructed by the research institute were relatively small, with the maximum AV and RV errors being less than 0.007 and 0.05, respectively, indicating good model performance. To further evaluate the performance of the model, six companies were randomly selected and evaluated for market value using the model constructed by the research institute, as well as the RV method, AV method, and enterprise-free cash flow evaluation method. The RV errors between the four methods and the actual results were compared. The experimental results are shown in Figure 8 [19].

From Figure 8, the AV error of the BP model proposed by the research institute was the smallest, at 14.90%, better than the general BP model. The RV error obtained using the relative estimation method was the highest, with a value of 22.93%. Among the market value estimates of seven enterprises, the focus technology company had the smallest RV error in the BP valuation method, with a value of 6.42%, and Wangsu Science & Technology had the largest value, with a value of 18.46%. In addition, compared to the other three evaluation models, the AV method ranked second with an ARE of 15.02%, which was 0.12% higher than they are of the BP valuation method constructed by the research institute. The model is

### Table 3. Combination weight results.

<table>
<thead>
<tr>
<th>Primary indicators</th>
<th>Secondary indicator</th>
<th>Secondary indicator weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Enterprises size</td>
<td>Total asset X1</td>
<td>0.0402</td>
</tr>
<tr>
<td></td>
<td>The total number of employees in the enterprises X2</td>
<td>0.0391</td>
</tr>
<tr>
<td></td>
<td>Total sales X3</td>
<td>0.0596</td>
</tr>
<tr>
<td>Enterprises benefit</td>
<td>Net operating profit margin X4</td>
<td>0.0372</td>
</tr>
<tr>
<td></td>
<td>Return on total assets X5</td>
<td>0.0459</td>
</tr>
<tr>
<td></td>
<td>Net return on assets X6</td>
<td>0.0291</td>
</tr>
<tr>
<td></td>
<td>Year-on-year growth ratio of total operating revenue X7</td>
<td>0.0862</td>
</tr>
<tr>
<td>Corporate financial ability</td>
<td>Current rate X8</td>
<td>0.0435</td>
</tr>
<tr>
<td></td>
<td>Quick rate X9</td>
<td>0.0423</td>
</tr>
<tr>
<td></td>
<td>Asset liability rate X10</td>
<td>0.0220</td>
</tr>
<tr>
<td>Enterprises growth</td>
<td>Fixed asset turnover X11</td>
<td>0.1263</td>
</tr>
<tr>
<td></td>
<td>Total asset growth ratio X12</td>
<td>0.0777</td>
</tr>
<tr>
<td></td>
<td>A net profit margin of sum asset X13</td>
<td>0.0625</td>
</tr>
<tr>
<td></td>
<td>Brand value X14</td>
<td>0.1152</td>
</tr>
<tr>
<td>Enterprises tech ability</td>
<td>R&amp;D personnel ratio X15</td>
<td>0.0730</td>
</tr>
<tr>
<td></td>
<td>The ratio of R&amp;D investment to sum sale X16</td>
<td>0.1035</td>
</tr>
</tbody>
</table>
applied to predict and assess the marketing competitiveness of all B2B ECC. The experimental results are shown in Figure 9.

From Figure 9, Hikvision ranked first in marketing competitiveness with a competitiveness value of 0.4393, and Wangsu Science & Technology ranked second with a competitiveness value of 0.4242, 0.0151 less than Hikvision ranked first. Ruimaotong ranked third with a competitiveness value of 0.3189, and the competitiveness scores of the other 20 companies were all below 0.30. The BP model was used to compare the marketing competitiveness of four enterprises in the e-commerce service

![Figure 7](image1.png)

**Fig. 7.** Error results between expected and actual values.

![Figure 8](image2.png)

**Fig. 8.** The RV Error results between the four methods and the actual results.

![Figure 9](image3.png)

**Fig. 9.** Evaluation results of marketing competitiveness of 23 enterprises using BP model.
industry, namely Wangsu Science & Technology, Autostar, Baoxin Software and Zhejiang University Wangxin, on the secondary indicators. The experimental results are shown in Figure 10.

It was understood that the scale of these four enterprises was roughly similar in 2016. From Figure 10, compared with the other three companies, Wangsu Science & Technology would have greater expectations in operating net profit, total return on assets, return on net asset, quick rate, total net asset profit, brand value and the ratio of R&D investment in total sales. The secondary competition indicators were 0.72, 0.43, 0.45, 0.28, 0.08, 0.10, and 0.06, respectively. In combination with the actual situation, Wangsu Science & Technology’s services tended to provide technology development and innovation services, so its users would cover websites, online game enterprises and operators. Among the other three companies, the expected value scores of each indicator were relatively uniform. Alteka had the highest score on the year-on-year growth rate of gross operating income, but there were no particularly outstanding projects, which might be related to its service type: Alteka was a professional manufacturer of automotive air conditioning compressors integrating research, development, production and sales, and its customer type was far less than Wangsu Science & Technology. The nature of the company’s services also required it to allocate competitive indicators as evenly as possible. The expected value scores of Baoxin Software and Zhejiang University Xinwang were similar. The higher expected value scores of the secondary competition index were the total assets’ Profit margin, and their expected competitiveness values were 0.038 and 0.040 respectively. Overall, based on the data of the above 23 companies, the evaluation performance of the model, the AV method and the enterprise free cash flow assessment method are shown in Table 4.

In Table 4, overall, the research method had the best evaluation performance, with an accuracy rate of 86%, followed by the AV method, with an accuracy rate of 85%, while the RV method had the lowest accuracy rate. Thus, the performance of the research method was better.

### 5 Conclusion

To overcome the shortcomings of traditional evaluation methods in assessing the marketing competitiveness of B2B ECC, a study proposed an optimized BPNN model for evaluating the marketing competitiveness of enterprises. By adjusting the number of hidden layers in the BP, a competitiveness evaluation model was drawn using Matlab tools. The research outcomes expressed that the BPNN constructed by the research institute had good learning and training ability when the learning parameter of the estimation model was 0.1. By combining the BP estimation model with subjective and objective weights, the weights of the second-level competitiveness indicators were obtained, with the maximum being the fixed asset turnover rate of 0.1263. The second was brand value with a weight value of 0.1152, and the third was the proportion of R&D investment to total sales with a weight value of 0.1035. The weight values of the other second-level indicators were all below 0.10. The maximum AV error of the model was 0.1152, and the third was the proportion of R&D investment to total sales with a weight value of 0.1035. The weight values of the other second-level indicators were all below 0.10. The maximum AV error of the model was 0.0006, and the maximum RV error was 0.0045. Compared with the traditional three market value estimation methods, the BP model had the highest accuracy, with an ARE of 14.90%, which was 0.12% higher than the high-performance AV method. The top 23 companies in terms of marketing competitiveness predicted by the model were Hikvision, with a competitiveness value of 0.4393. The BP model was used to further subdivide the competition score of enterprises’ secondary indicators. Among the selected

![Fig. 10. BP model for predicting secondary competition indicator values of four enterprises.](image-url)
experimental objects, Netsux Technology had higher scores in terms of competitiveness in terms of net profit, total return on asset, return on net asset, quick ratio, net profit of total assets, and the proportion of brand value and R&D investment in total sales, which were 0.72, 0.43, 0.45, 0.28, 0.08, 0.10, and 0.06, respectively. The experimental findings indicated that the BP constructed by the research institute had a good performance in predicting the marketing competitiveness of B2B ECC. However, because of the relatively high sample data selected and the focus of the study only on enterprise-related factors that affect marketing competitiveness, without considering environmental changes, there is some room for improvement.

References

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