Reverse Logistics Enterprise Performance Research Based on Super-Efficiency DEA and LMBP Neural Network

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Abstract. On the basis of considering the characteristics of reverse logistics enterprises, this paper uses stakeholder theory to establish an evaluation system containing 36 indicators in five dimensions, based on the balanced scorecard, and adopts PCA optimization index. In view of the performance evaluation problem, first, the performance data is obtained by using the super-efficiency DEA, then the enterprise performance of A company is fitted by LMBP neural network to obtain the quantitative model of performance evaluation, and finally, according to the resulting weight reference performance benchmark, the direction of reverse logistics enterprise performance improvement is given. The simulation results show that the index system can react to the reverse logistics characteristics very well, and the BP neural network based on LM algorithm can accurately and efficiently evaluate the performance of reverse logistics enterprises which has better generalization, and can find out the key performance indicators and give reasonable optimization direction for enterprises by reverse tracking the weights of the neural network.

Keywords. Reverse logistics; BSC; super-efficiency DEA; LMBP neural network.

1. Introduction
The researchers’ research on reverse logistics performance evaluation focuses on the difference between object selection, evaluation index system and evaluation method, and although the characteristics of the product particularity of reverse logistics enterprises are considered in the index system, they do not consider the sustainable development performance of enterprises under the background of comprehensive utilization of resources, and the determination of the special attributes of reverse logistics is not clear. In the choice of methods, static methods make the evaluation system generalization ability is weak, the promotion ability is poor and the cost is high. Therefore, this paper considers the particularity of reverse logistics enterprises, and builds a scientific and effective quantitative model with the help of super-efficiency DEA and LMBP neural network, which makes the method popularized to similar reverse logistics enterprise performance evaluation quickly, effectively and low cost, and can provide reference for improving enterprise performance.

2. Literature Review
At present, the attention to reverse logistics at home and abroad is gradually increasing, but there is still a lack of effective research on the performance evaluation of reverse logistics enterprises and more attention to the object, index system and evaluation methods. In objects, Zeng [1] selected a scrap car enterprise to carry out empirical research on performance evaluation, Hao [2] discusses the feasibility
of recycling end-of-life vehicle batteries. The residual value of waste products is an important criterion for recycling or not, so Maheswari [3], targeting informal e-waste enterprises in Indonesia, has established a sustainable reverse logistics performance measurement credit card model. In the establishment of the index system, because the performance of reverse logistics enterprises is a multi-objective complex, Xiao [4] constructed a comprehensive evaluation index system based on the “3R” principle of circular economy. Meng [5] takes consider the seasonal characteristics of the garment supply chain, taking into account the flexible criteria. Chaves [6] also included the relationship between reverse logistics enterprises and economic sectors into the evaluation index system. Sangwan [7] established a key indicator system for performance evaluation based on the basic activities of the reverse logistics. In methods, Shaik [8] combines DEMATEL, Fuzzy ANP and hierarchical analysis to form a new evaluation method. Han [9] used TOPSIS and FLINTSTONES to generate a comprehensive evaluation result based on expert evaluation. From the point of view of quantitative evaluation, fuzzy evaluation method, TOPSIS, DEA and machine learning methods are more commonly used in reverse logistics enterprise performance evaluation. For example, Yang [10] uses SEM model based on machine learning technology to evaluate the competitiveness of logistics enterprises.

3. The Establishment of the Indicator System
The premise of reasonable evaluation of enterprise performance is to establish an accurate and reasonable performance evaluation index system. The current performance evaluation index system can not fully reflect the characteristics of reverse logistics enterprises, such as balanced scoring method and EVA evaluation method [11], also does not take into account the development of enterprises in the context of comprehensive utilization of resources and strengthening of social environmental awareness. And in the process of enterprise’s actual operation, many enterprises neglect the maximization of social welfare and environmental sustainability in order to maximize the interests of shareholders, which damages the corporate image, thus affecting the long-term benefits and development of enterprises.

With the help of stakeholder theory, considering the product particularity and sociality of reverse logistics enterprises, based on BSC thought from the financial, internal process, customer, innovation development, social five dimensions of a total of 36 indicators to design the reverse logistics enterprise performance evaluation system (table 1). some indicators of the design reference to the research results [1, 2, 4].

4. Super-Efficiency DEA and LMBP Neural Networks
4.1. Introduction to the Super-Efficiency DEA
In order to solve the problem that traditional DEAs have multiple units that are valid at the same time and cannot be compared between multiple valid units, Andersen.P and Petersen.N .C further improve the super-efficiency DEA model. Suppose there are n objects, each object is marked as DMU, and each DMU has m inputs and s outputs. \( x_i \) represents DMU_i’s item i input and \( y_j \) represents DMU_i’s j output. Therefore, the input of the i DMU and the output of the j DMU are expressed as:

\[
x_i = (x_{i1}, x_{i2}, \ldots, x_{in})^T, \quad (i=1,2,\ldots,n).
\]

\[
y_j = (y_{j1}, y_{j2}, \ldots, y_{jn})^T, \quad (j=1,2,\ldots,n).
\]

Then the super-efficiency DEA model is:

\[
\begin{align*}
\text{Super Efficiency DEA} & \quad \min \theta \\
& \quad \text{s.t. } \sum_{i \in I_k} x_i \lambda_i \leq \theta x_e \\
& \quad \sum_{j \in J_k} y_j \lambda_j \geq y_i \\
& \quad \lambda_i \geq 0, \; i = 1,2,\ldots,n
\end{align*}
\]
Table 1. Based on BSC’s five-dimensional comprehensive evaluation index system.

| Dimension               | Index                              | Quality | Code | Dimension               | Index                              | Quality | Code |
|-------------------------|------------------------------------|---------|------|-------------------------|------------------------------------|---------|------|
| Finance                 | Asset-liability ratio             | Ration  | A1   | Customer                | Market share                       | Qualitative | C1   |
|                         | Return on assets                  | Ration  | A2   | Customer complaints     | Ration                             | C2       |
|                         | Return on equity                  | Ration  | A3   | Customer retention rate | Ration                             | C3       |
|                         | Operating margin                  | Ration  | A4   | Capital preservation    | Ration                             | D1       |
|                         | Main business revenue             | Ration  | A5   | and appreciation rate  | Ration                             | D2       |
|                         | Main business cost                | Ration  | A6   | Growth rate of total    | Ration                             | D2       |
|                         | Transportation costs              | Ration  | A7   | assets                 | Ration                             | D3       |
|                         | Cost of using environmentally     | Ration  | A8   | Sustainable growth      | Ration                             | D3       |
|                         | friendly equipment                |         |      | rates                  | Ration                             | D4       |
|                         | Waste product recovery cost rate  | Ration  | A9   | Profit growth rate      | Ration                             | D4       |
|                         | Operating cycle                   | Ration  | B1   | Proprietary technology  | Ration                             | D5       |
|                         | Technology input ratio            | Ration  | B2   | value                   | Ration                             | D6       |
| Internal processes      | Total asset turnover              | Ration  | B3   | The number of patents  | Ration                             | D7       |
|                         | Customer Concentration            | Ration  | B4   | Technology input ratio  | Ration                             | D8       |
|                         | Herfindahl Index                  |         |      |                         |                                     | E1       |
|                         | Supplier concentration            | Ration  | B5   | Environmental input     | Ration                             | E2       |
|                         | Herfindahl index                  |         |      |                         |                                     | E1       |
|                         | Supply Chain Concentration        | Ration  | B6   | Tax status              | Ration                             | E2       |
|                         | Cost rate for e-waste disposal    | Ration  | B7   | Government support      | Qualitative                         | E5       |
|                         | Material reuse rate               | Ration  | B8   | Whether to pass         | Qualitative                         | E5       |
|                         | Disassembly technology level      | Qualitative | B9 | iso14001                |                                     |          |

4.2. LMBP Algorithm Principle

BP neural network contains an input and output layer and one or more implied layers. The gradient drop method used by the traditional BP neural network is fast and efficient in the initial calculation, but with the gradual approach to the optimal value, it is easy to fall into the local minimum value, instead of global optimal solution. To this end, the researchers based on the LM algorithm proposed an improved LMBP neural network algorithm and effectively overcome the traditional BP algorithm follow-up convergence speed is slow, easy to fall into the problem of local optimal solution [12]. In the LMBP algorithm, based on the principle of decreasing error, the initial weight and threshold are constantly adjusted, and the goal of global optimization is finally achieved. The iterative correction formula for weights and thresholds can be represented as 

$$w^{k+1} = w^k + \Delta w, \Delta w = -[J^T(\Delta x)J(\Delta x) + \mu^2]^{-1}J(\Delta x)$$.

Learning rate $\mu > 0$ is constant and $I$ is a matrix in units. When $\mu = 0$, the LM algorithm is Gaussian Newtonian. When $\mu \to \infty$ is the gradient drop method. A large number of applications have proved that the LM algorithm computational speed can be greatly improved compared with the gradient drop method. And because $[J^T(\Delta x)J(\Delta x) + \mu^2]^{-1}$ is always positive, the solution of $\Delta w$ in the LM algorithm always exists.
5. Case Analysis
Listed company A is one of the leading enterprises in the economical and large-scale recycling of electronic waste and used batteries in China. Based on its publicly disclosed information and Cathay Pacific database, the data for 2011-2020 are analyzed in this paper.

5.1. The indicator system
Because the original index system has a total of 36 secondary indicators, some indicators are more linear, so the use of PCA simplifies the original indicators. Before analyzing the main components, standardize the raw data to eliminate the effects of different scales. Then the PCA is used to simplify the index, select the component with the characteristic value greater than 1, stop the selection when the cumulative contribution rate reaches 80%. The principal components obtained are shown in table 2.

### Table 2. Principal components after PCA screening.

| Dimension      | Ingredients | Eigenvalue | Cumulative % | Dimension      | Ingredients | Eigenvalue | Cumulative % |
|----------------|-------------|------------|--------------|----------------|-------------|------------|--------------|
| Financial      | 1           | 6.24249    | 69.36        | Internal       | 1           | 8.33415    | 92.6         |
|                | 2           | 1.16512    | 82.31        | processes      | 1           |            |              |
| Innovation     | 1           | 5.52952    | 61.44        | Customer       | 1           | 2.75099    | 91.7         |
| and Development| 2           | 1.62256    | 79.47        | Social         | 2           | 1.39397    | 65.42        |
|                | 3           | 1.35367    | 94.51        |                | 3           | 1.12124    | 84.11        |

According to the load matrix to obtain the main component contribution rate, select a higher contribution rate and positive indicators, 5 primary indicators 36 secondary indicators finally reduced to 5 primary indicators 29 secondary indicators and as an input indicator.

5.2. Super Efficiency DEA Performance Judgment
According to the above-mentioned indicator system, four input indicators including main business cost, environmental protection equipment use cost, development expenditure, environmental protection investment and three output indicators including operating profit rate, total asset turnover rate, and sustainable growth rate are selected to evaluate performance. Input-oriented, assuming that the scale can be variable use of radial super-efficiency model Super-DEA-V, and finally get the efficiency score of A enterprise, according to the upper and lower boundaries of the score will be divided into four intervals and corresponding to the corresponding performance level: \([0,0.5)\) - poor; \([0.05,1)\) - general; \([1.1.5)\) - good; \([1.5,2)\) - Excellent. The final evaluation can be found in table 3.

### Table 3. The results of the super-efficiency DEA evaluation.

| DMU | Efficiency Result | DMU | Efficiency Result |
|-----|-------------------|-----|-------------------|
| 2011| 1.509362 Excellent | 2016| 1.0019075 General |
| 2012| 1.2883173 General  | 2017| 1.1615322 General |
| 2013| 1.1512493 General  | 2018| 1.0557653 General |
| 2014| 1.0898346 General  | 2019| 1.0226301 General |
| 2015| 0.4687155 Poor     | 2020| 0.3298229 Poor     |

The data of the super-efficiency DEA evaluation results were incorporated into the LMBP neural network as the raw data source. Poor, general, good, excellent four performance levels are coded as s1, 2, 3, 4, and supply chain performance as an output indicator.
5.3. LMBP Neural Network Training

5.3.1. Determine the Network Structure and Number of Nodes. According to Kolmogorov’s theory, a three-tiered network can approximate any continuous function, so this paper establishes a three-tier network structure with an implied layer. The study contains a total of 29 input indicators and 1 output indicator, so the input node is set to 29 and the output node is set to 1. The selection of the number of implied layer nodes refers to the empirical formula \( t = \sqrt{m+n+a} \). Wherein, \( t \) is the number of implied layer nodes, \( m \) is the number of input nodes, \( n \) is the number of output nodes, \( a \) is a constant of 1-10, so the number of implied layer nodes in this paper is selected between 5-15.

5.3.2. Determine the Network Parameters. For the selection of the transfer function, the S-type transfer function is able to convert the input parameters from negative infinity to positive infinity to output between \([-1,1]\). Its main contents include Tansig-double-tangent S-type transport function and Logsig-logs types function. For the expression of linear relationships, the Purelin linear function can be used. Matlab’s neural network toolbox is used to generate a neural network structure with one implied layer, setting the maximum number of training sessions at 1000, the learning rate at 0.01, the minimum error at 0.00001, and the training function at tramlm. The errors of different transfer functions are shown in table 4.

| Transfer function | L-L | L-T | L-P | T-T | T-L | T-P | P-P | P-T | P-L |
|-------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| epoch             | 8   | 7   | 6   | 7   | 6   | 3   | 3   | 5   | 9   |
| MSE               | 2.95E-06 | 3.51E-06 | 1.22E-09 | 6.39E-06 | 1.67E-01 | 2.16E-10 | 2.34E-12 | 4.42E-06 | 6.09E-07 |

5.3.3. Instance Simulation Prediction. Using the data for 2011-2017 as training data and the data for 2018-2020 as the test data, after many experiments, it was determined that the transfer functions were Tansig and Purelin, the training functions were trained as trainlm, and the number of implied layer nodes was 5. After training, \( R \) is approaching 1, indicating that the model fits very well and can be used as a performance evaluation, fitting effect is shown in figure 1.

The trained neural network model was used in the performance prediction experiment of A enterprise 2011-2020, after 3 iterations, MSE reached 5.85e-09, and the error between the simulation value and the real value was less than 10%, which shows that the model can get a better fit effect in a short period of time, which is accurate, effective and efficient, simulation result is shown in table 5.

5.4. Results Analysis

The neural network has been trained to better fit the performance of A enterprises, and the network weight can reflect the intrinsic relationship between the indicators and the final performance. Therefore, the weight after training is extracted as the influence coefficient of each index in the performance evaluation model. According to the neural network structure along the output node - implied layer node - input node reverse analysis, LMBP neural network weight represents the degree of influence of each factor on the final evaluation results, according to the calculation results can be derived from the distribution of the weight of the implied layer to the output layer, 5 implied layers The weights corresponding to the nodes are 0.1906, -0.2891, -0.7710, 0.9137, -0.9865, and the evaluation model for the final performance is quantified as:

\[
y = 0.1906x_1 - 0.2891x_2 - 0.7710x_3 + 0.9137x_4 - 0.9865x_5
\]

(3)

\( y \) is the final performance level, \( x_i \) is the implied layer node, it can be seen that the \( x_5 \) coefficient is -0.9865, is the most influential to the results of the implied layer node, here is selected this node as an example of the analysis object.
By extracting the weights from the input layer to the implied layer, the weight calculation of the effect of 29 arguments on the node is obtained. According to equation (4), supplier concentration Herfindahl index $C_i$, technician ratio $D_i$ and environmental input $E_i$ three indicators have a greater impact on the final result and negative impact on the final performance. If an enterprise wants to adjust the level of business to achieve better supply chain performance, reduce supplier concentration, lower the proportion of technical personnel and environmental input can make the enterprise’s input-output ratio better.

6. Conclusions
Based on BSC, this paper establishes a comprehensive index system based on stakeholder theory, combines the super-efficiency DEA with the LMBP-based neural network to have objective evaluation results and better promotion ability, which can provide reference for the evaluation of the performance
of reverse logistics enterprises. The presentation of quantitative model can provide reference for the evaluation of the performance of reverse logistics enterprises. However, due to the difficulty of data collection, there are few samples in this paper, which can affect the accuracy of simulation results. The LMBP neural network is not reproducible due to the randomness of the initial weight assignment, and it needs to repeat the experiment many times in order to get a good neural network structure. Therefore, subsequent studies can consider improving the selection of indicators for the super-efficiency DEA model, increasing the sample size, and improving the accuracy and operability of predictions.

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