



Research Article

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Research on the evaluation of collaborative logistics performance oriented manufacturing industry based on AHP-BP model

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ABSTRACT

Building an indicator system of collaborative logistics performance oriented manufacturing industry using the Balanced Scorecard, this paper puts forward 20 evaluation indicators from five aspects, the level of information, business process, finance, customer service ability, learning and development which builds the model of collaborative logistics performance oriented manufacturing industry based on AHP and BP neural network. The model makes analysis with AHP on collaborative logistics performance indicators for Wen ling automobile and motorcycle manufacturing industry and treats the AHP evaluation results as the training and testing data which will be input into network model to train and simulate test. The results show that the evaluation method of collaborative logistics performance oriented manufacturing industry based on AHP and BP neural network is reasonable and feasible. It is worthy of spreading in the related field of the performance evaluation.

Keywords: Collaborative logistics; Performance; AHP; BP neural network

INTRODUCTION

Collaborative logistics, throughout the entire production process, pursues internal logistics, external logistics and shipping logistics and so on to meet the needs of customers and provide professional, timely, efficient logistics services. We wish to achieve the logistics optimization goal of reducing logistics cost and improving the customer satisfaction. In oriented manufacturing management environment, logistics performance is an important part of manufacturing overall performances and should try to integrate and optimize the logistics resources so that to promote the overall logistics performance and also enhance the market competitive capability of manufacturing and competitive advantage.

At present, the domestic and foreign related researches are mainly about performance evaluation of the third party logistics and supply chain. Liu H T and Wang W K [1] put forward by using comprehensive fuzzy evaluation method to choose the third party logistics providers. Yang Dequan and Pei JinYing [2] proposed DEA and AHP method to evaluate the logistics system which effectively combined the advantages of the two methods and made up for the lack of a single method. Chen Dongdong and Peng Jiyuan [3] used factor analysis method to performance evaluation and sorting of supply chain, in order to grasp the key factors which had influence to the performance of supply chain and helped the enterprise decision makers make scientific and rational decision. Wu Yisheng [4], through the study of enterprise logistics performance evaluation, proposed an instructional theory framework of how manufacturing enterprise made application to logistics performance evaluation theory from the system and the whole point of view. But Wu discussed in theory, not from the concrete method to apply and promote. So the paper firstly builds collaborative logistics performance indicators system for manufacturing by using the Balanced Scorecard and then makes a model of collaborative logistics performance oriented manufacturing industry based on AHP-BP. Afterwards, the paper makes Wen Ling automobile manufacturing industry as an example to apply and promote, which helps manufacturing enterprises gain a competitive advantage, improve enterprise performance, and also make supplement for the evaluation of enterprise logistics performance theory in a certain extent.

2. Build the model of collaborative logistics performance oriented manufacturing industry based on AHP-BP

The performance indicator of collaborative logistics performance oriented manufacturing industry, has the characteristics of the complexity, uncertainty and a large number of quantity. And at the same time, it has the features of nonlinear correlation between each other. Based on this, this paper integrates the analytic hierarchy process (AHP) combined with BP neural network for comprehensive evaluation. The analytic hierarchy process supported by expert system, can deal with the combination of qualitative and quantitative problem and also can make the subjective judgment and policy experience from decision makers into the model which realize quantitative processing. BP neural network has the ability of associative inference, high-speed parallel processing, adaptive identification and simulating human thinking which can be able to find the nonlinear mapping relationship between input-output after scientific training and study. BP neural network has the great advantages to intelligently infer and predict and the disadvantage of that the network training process inevitably exists nonlinear programming as result to fall into local minimum point. So this paper combining the subjective evaluation and objective evaluation, uses analytic hierarchy process (AHP) to give the weight of the indicator system so as to make up the defect in any assignment of weights of neural network and to reduce the probability of its computation trapped in local minima[5].

This model firstly determines the indicator weight using AHP method in the performance indicator system and treats the results as the inputs of BP neural network. Afterwards, we can get the output results and then build the model BP neural network.

The model of BP neural network uses the sample data for training and when the accuracy requirements are finally met the accuracy requirements, the paper makes simulation of the corresponding data by fitting a good network to get the collaborative logistics performance evaluation results to be evaluated for manufacturing industry.

2.1 Build the hierarchical model of collaborative logistics performance oriented manufacturing industry

The hierarchical structure model generally is divided into three layers, namely the target layer, criterion layer and indicator layer. Establishment of logistics performance evaluation indicator system is based on Balanced Scorecard. After the discussion from the expert group, we build evaluation indicator system from five aspects. See table 1.

Table 1 An indicator system of collaborative logistics performance oriented manufacturing industry

Target layer	Criterion layer	Indicator layer
Collaborative logistics operation performance manufacturing oriented comprehensive evaluation u	$u_1^{(1)}$ The level of information	Customer service information system for completeness $u_{11}^{(2)}$
		Information transmission efficiency $u_{12}^{(2)}$
		System operator for information system of management level $u_{13}^{(2)}$
		Cargo tracking capabilities $u_{14}^{(2)}$
	$u_2^{(1)}$ Business process	Inventory turnover rate $u_{21}^{(2)}$
		Inventory loss rate $u_{22}^{(2)}$
		The utilization rate of per unit area $u_{23}^{(2)}$
		The effective work of transportation equipment $u_{24}^{(2)}$
	$u_3^{(1)}$ Finance	The human cost $u_{31}^{(2)}$
		The logistics cost $u_{32}^{(2)}$
		Operating costs $u_{33}^{(2)}$
		Logistics assets management level $u_{34}^{(2)}$
	$u_4^{(1)}$ Customer service ability	On time delivery rate $u_{41}^{(2)}$
		Accuracy of delivery rate $u_{42}^{(2)}$
		The quality and safety of goods rate $u_{43}^{(2)}$
		Complaints handling rate $u_{44}^{(2)}$
	$u_5^{(1)}$ Learning and development	Ability of logistics personnel $u_{51}^{(2)}$
		Staff training rate $u_{52}^{(2)}$
		Maintenance rate of information system $u_{53}^{(2)}$
		The new technology application success rate $u_{54}^{(2)}$

2.2 Build the model of BP neural network

The application of BP neural network for performance evaluation is essentially based on the process of training data

for Boolean vector approximation [6]. In this paper, the BP network is a kind of multilayer feedforward neural network and its neurons in the conversion function is nonlinear sigmoid function, $f(x)=1/(1+e^{-x})$.

(1) Determine the level of the BP network. Theoretically it is approximately arbitrary precision of a mapping from input to output. So a three-layer BP neural network can complete any N to M dimensional mapping and we usually choose BP network with a single hidden layer network[7].

(2) Determine the node number of the input and output layer of the BP network. The external description problem determines number of nodes in the network's input and output neurons. The number of input layer nodes and the indicator number of collaborative logistics performance evaluation should be the same. Using 20 indicators of collaborative logistics operation performance manufacturing oriented to simulated evaluation, so the network input layer node number is 20. The collaborative logistics performance evaluation value oriented manufacturing is the network output, namely, so the output node number is 1.

(3) Determine the number of nodes in the hidden layer. The primary node number can be calculated according to the formula $n_H=(n_I+n_O)^{1/2}+L$ or $h=\log_2 N$ to determine the scope of the general (n_H represents the hidden layer node number, n_I represents input layer node number, n_O represents the output layer node number, L is an integer between 1 to 10). This network hidden layer 8 is finally determined.

EXPERIMENTAL SECTION

3 Application example analysis of AHP-BP in collaborative logistics performance evaluation oriented manufacturing

3.1 Calculation weight of AHP hierarchical structure and each indicator

(1) Build judgment matrix.

As for the collaborative logistics performance evaluation indicator system oriented manufacturing, invite experts and professors in the related field to score the evaluation indicator system of evaluation. These experts and professors include the three logistics association expert in Tai Zhou, two experts of logistics and purchasing association in Zhejiang province, two senior leaders who have a leading in collaborative of logistics enterprises and manufacturing enterprises in Wen Ling city and a senior leader who studies on logistics enterprises and manufacturing enterprises. The totally 10 questionnaires are sent out and 10 are taken back. The recovery rate is 100%. At last, we make data collection and sort to calculate all levels of judgment matrix as followed.

$$u = \begin{bmatrix} 1 & 1/3 & 1/4 & 1/3 & 2 \\ 3 & 1 & 1/2 & 3 & 4 \\ 4 & 2 & 1 & 2 & 4 \\ 3 & 1/3 & 1/2 & 1 & 2 \\ 1/2 & 1/4 & 1/4 & 1/2 & 1 \end{bmatrix} u_1^{(1)} = \begin{bmatrix} 1 & 1/3 & 1/2 & 1/4 \\ 3 & 1 & 2 & 2 \\ 2 & 1/2 & 1 & 1/2 \\ 4 & 1/2 & 2 & 1 \end{bmatrix} u_2^{(1)} = \begin{bmatrix} 1 & 1/2 & 3 & 1/2 \\ 2 & 1 & 3 & 3 \\ 1/3 & 1/3 & 1 & 1/2 \\ 2 & 1/3 & 2 & 1 \end{bmatrix}$$

$$u_3^{(1)} = \begin{bmatrix} 1 & 1/4 & 1/2 & 2 \\ 4 & 1 & 4 & 3 \\ 2 & 1/4 & 1 & 3 \\ 1/2 & 1/3 & 1/3 & 1 \end{bmatrix} u_4^{(1)} = \begin{bmatrix} 1 & 1/2 & 1/3 & 2 \\ 2 & 1 & 1/2 & 3 \\ 3 & 2 & 1 & 4 \\ 1/2 & 1/3 & 1/4 & 1 \end{bmatrix} u_5^{(1)} = \begin{bmatrix} 1 & 3 & 2 & 3 \\ 1/3 & 1 & 1/3 & 2 \\ 1/2 & 3 & 1 & 4 \\ 1/3 & 1/2 & 1/4 & 1 \end{bmatrix}$$

(2) All levels of indicator weight and consistency test

1) Determinate the weight of criterion layer

According to the above formula, we can get criterion layer factor relative weight as shown in table 2.

Table 2 Criterion layer factor relative weights

Factor	$u_1^{(1)}$	$u_2^{(1)}$	$u_3^{(1)}$	$u_4^{(1)}$	$u_5^{(1)}$
Weight	0.0923	0.2934	0.3781	0.1646	0.0716

At the same time, we can get $\lambda_{MAX}=5.2118$, $CI=0.0529$, $CR=0.0473 < 0.1$. As a result, this judgment matrix is completely consistent and the weights are in the acceptable range.

2) Determinate the weight of indicator layer. With the same method, we can calculate judgment matrix, characteristic value vector, the biggest characteristic root and consistency test as showed in table 3-7.

Table 3 Indicator layer ($u_{11}^{(2)} - u_{14}^{(2)}$)

Indicator layer	$u_{11}^{(2)}$	$u_{12}^{(2)}$	$u_{13}^{(2)}$	$u_{14}^{(2)}$	Calculation results
$u_{11}^{(2)}$	1	1/3	1/2	1/4	$w=(0.0989,0.4074,0.1841,0.3096)^T$ $\lambda_{MAX}=4.0963$ $CI=0.0321$ $CR=0.0361<0.1$
$u_{12}^{(2)}$	3	1	2	2	
$u_{13}^{(2)}$	2	1/2	1	1/2	
$u_{14}^{(2)}$	4	1/2	2	1	

Table 4 Indicator layer ($u_{21}^{(2)} - u_{24}^{(2)}$) judgment matrix judgmentmatrix

Indicator layer	$u_{21}^{(2)}$	$u_{22}^{(2)}$	$u_{23}^{(2)}$	$u_{24}^{(2)}$	Calculation results
$u_{21}^{(2)}$	1	1/2	3	1/2	$w=(0.2045,0.4527,0.1067,0.2361)^T$ $\lambda_{MAX}=4.2148$ $CI=0.0716$ $CR=0.0804<0.1$
$u_{22}^{(2)}$	2	1	3	3	
$u_{23}^{(2)}$	1/3	1/3	1	1/2	
$u_{24}^{(2)}$	2	1/3	2	1	

Table 5 Indicator layer ($u_{31}^{(2)} - u_{34}^{(2)}$) judgment matrix

Indicator layer	$u_{31}^{(2)}$	$u_{32}^{(2)}$	$u_{33}^{(2)}$	$u_{34}^{(2)}$	Calculation results
$u_{31}^{(2)}$	1	1/4	1/2	2	$w=(0.1434,0.5338,0.2244,0.0984)^T$ $\lambda_{MAX}=4.2199$ $CI=0.0733$ $CR=0.0824<0.1$
$u_{32}^{(2)}$	4	1	4	3	
$u_{33}^{(2)}$	2	1/4	1	3	
$u_{34}^{(2)}$	1/2	1/3	1/3	1	

Table 6 Indicator layer ($u_{41}^{(2)} - u_{44}^{(2)}$) judgement matrix

Indicator layer	$u_{41}^{(2)}$	$u_{42}^{(2)}$	$u_{43}^{(2)}$	$u_{44}^{(2)}$	Calculation results
$u_{41}^{(2)}$	1	1/2	1/3	2	$w=(0.1603,0.2776,0.4668,0.0953)^T$ $\lambda_{MAX}=4.0310$ $CI=0.0103$ $CR=0.0116<0.1$
$u_{42}^{(2)}$	2	1	1/2	3	
$u_{43}^{(2)}$	3	2	1	4	
$u_{44}^{(2)}$	1/2	1/3	1/4	1	

Table 7 Indicator layer ($u_{51}^{(2)} - u_{54}^{(2)}$) judgment matrix

Indicator layer	$u_{51}^{(2)}$	$u_{52}^{(2)}$	$u_{53}^{(2)}$	$u_{54}^{(2)}$	Calculation results
$u_{51}^{(2)}$	1	3	2	3	$w=(0.4324,0.1441,0.3286,0.0949)^T$ $\lambda_{MAX}=4.1320$ $CI=0.0440$ $CR=0.0494<0.1$
$u_{52}^{(2)}$	1/3	1	1/3	2	
$u_{53}^{(2)}$	1/2	3	1	4	
$u_{54}^{(2)}$	1/3	1/2	1/4	1	

From the table 3-7, the secondary indicator layer CR is less than 0.10, so all of these are through the consistency test.

3) Hierarchy total sorts

Table 8 Collaborative logistics performance evaluation indicator system of weights oriented manufacturing

Criterion layer	Indicator layer	Weights
$u_1^{(1)}$	$u_{11}^{(2)}$	0.0091
	$u_{12}^{(2)}$	0.0376
	$u_{13}^{(2)}$	0.0170
	$u_{14}^{(2)}$	0.0286
$u_2^{(1)}$	$u_{21}^{(2)}$	0.0600
	$u_{22}^{(2)}$	0.1328
	$u_{23}^{(2)}$	0.0313
	$u_{24}^{(2)}$	0.0693
$u_3^{(1)}$	$u_{31}^{(2)}$	0.0542
	$u_{32}^{(2)}$	0.2018
	$u_{33}^{(2)}$	0.0849
	$u_{34}^{(2)}$	0.0372
$u_4^{(1)}$	$u_{41}^{(2)}$	0.0264
	$u_{42}^{(2)}$	0.0457
	$u_{43}^{(2)}$	0.0768
	$u_{44}^{(2)}$	0.0157
$u_5^{(1)}$	$u_{51}^{(2)}$	0.0310
	$u_{52}^{(2)}$	0.0103
	$u_{53}^{(2)}$	0.0235
	$u_{54}^{(2)}$	0.0068

3.2 The training and simulation example of the BP neural network model

(1) Sample data

The sample data is through research from oriented manufacturing automobile collaborative logistics industry performance evaluation of Wen Ling city.

Panel of judges through the interview and the questionnaire survey on staff who are responsible for the logistics industry, makes performance score which has five grades, weaker, weak, normal, strong and very strong and the corresponding values are 1, 3, 5, 7, 9. We can get the performance ratings in table 9.

(2) The network training and data simulation

In the actual calculation, firstly, the indicator value should be standardized treatment and make all the data in table 9 divided by 10, with unified to [0, 1]. The first 16 sets of data used in the model of BP neural network learning and training, the rest of the other two groups to validate the precision of the model.

In the program, we give the learning accuracy $\varepsilon=0.000001$, the number of training $N=2000$, learning coefficient $lr=0.35$. With the help of Matlab software, gradient descent method is used for training. Finally, after 144 iterative adjustments, it finishes the test and meets the training requirements of precision. The result is shown in figure 1. At the same time, from the Figure 2, we can get the result that ideal tropic of cancer and the optimal regression line are basically-coincidence.

Table 9 The performance evaluation indicators score (specific value in the table)

Sample	The serial number	Evaluation indicators																				value
		$u_{11}^{(2)}$	$u_{12}^{(2)}$	$u_{13}^{(2)}$	$u_{14}^{(2)}$	$u_{21}^{(2)}$	$u_{22}^{(2)}$	$u_{23}^{(2)}$	$u_{24}^{(2)}$	$u_{31}^{(2)}$	$u_{32}^{(2)}$	$u_{33}^{(2)}$	$u_{34}^{(2)}$	$u_{41}^{(2)}$	$u_{42}^{(2)}$	$u_{43}^{(2)}$	$u_{44}^{(2)}$	$u_{51}^{(2)}$	$u_{52}^{(2)}$	$u_{53}^{(2)}$	$u_{54}^{(2)}$	
Train sample	1	9	9	7	9	9	9	9	7	9	7	9	9	9	9	5	7	3	3	5	5	7.7
	2	7	7	5	9	3	3	7	7	7	9	7	7	7	7	7	5	5	5	7	9	6.5
	3	7	5	3	5	5	5	5	7	5	5	5	7	3	5	5	7	9	5	7	5	5.3
	4	9	5	5	5	7	9	9	5	9	7	3	9	5	7	5	5	7	5	7	5	6.6
	5	5	5	9	5	5	5	5	5	5	3	5	7	5	5	7	7	7	9	5	3	5.0
	6	5	3	7	5	7	5	7	9	5	5	7	5	5	5	5	7	5	5	5	5	5.6
	7	3	7	3	7	5	5	5	5	5	5	3	7	3	5	5	3	7	7	5	5	5.0
	8	5	9	5	5	5	5	9	7	9	7	7	7	7	9	7	5	7	9	5	9	6.8
	9	5	7	5	5	5	3	7	5	5	5	5	3	5	5	5	7	5	3	5	7	4.8
	10	5	3	5	5	9	7	5	7	7	5	5	5	5	5	5	5	5	5	5	7	5.7
	11	9	5	9	5	7	7	5	9	7	7	3	9	7	5	7	5	7	7	7	7	6.6
	12	7	7	3	3	5	5	5	7	5	3	5	7	7	3	9	7	9	7	7	7	5.3
	13	7	9	9	9	3	3	9	7	9	9	9	9	9	9	5	5	5	3	7	3	7.0
	14	5	9	5	9	7	9	5	5	5	5	7	7	5	5	7	9	7	7	7	7	6.5
	15	5	5	9	7	9	9	5	5	7	5	3	7	5	5	5	5	5	5	3	5	5.9
	16	5	9	5	9	3	3	9	3	7	7	9	7	7	5	7	7	5	5	5	5	6.0
Inspect sample	17	9	3	3	5	3	5	5	5	7	5	3	3	5	5	9	7	3	9	7	5.1	
	18	7	7	7	9	5	3	7	7	9	5	7	9	7	7	7	5	3	5	7	7	6.0

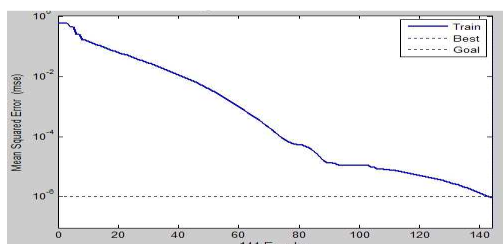


Fig.1 The network training error change curve

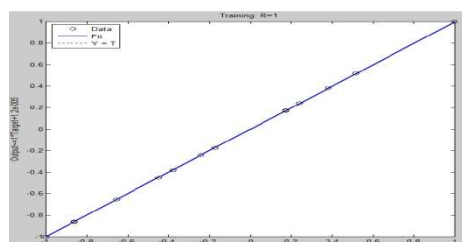


Fig.2 Actual output of training sample and ideal output of linear regression analysis

RESULTS AND DISCUSSION

From the error analysis of the learning outcomes of the table 10, the training results of BP neural network are almost consistent with the results of expert evaluation and error is within an acceptable range. So given the training sample learning has met the requirements.

Table 10 Study result error analysis

Serial number	1	2	3	4	5	6	7	8
The training results	0.7700	0.6501	0.5302	0.6600	0.5000	0.5598	0.4999	0.6803
Expected output	0.7700	0.6500	0.5300	0.6600	0.5000	0.5600	0.5000	0.6800
Relative error	0.0038%	0.0129%	0.0219%	0.0036%	0.0177%	0.0117%	0.0310%	0.0102%
Serial number	9	10	11	12	13	14	15	16
The training results	0.4801	0.5700	0.6598	0.5300	0.6998	0.6500	0.5901	0.5999
Expected output	0.4800	0.5700	0.6600	0.5300	0.7000	0.6500	0.5900	0.6000
Relative error	0.0027%	0.0200%	0.0045%	0.0171%	0.0029%	0.0068%	0.0088%	0.0045%

After the training, it makes use of trained three-layer BP network and checks the input data respectively. The result is shown in table 11.

Table 11 The error analysis of the test results

The serial number	17	18
The training results	0.4847	0.6973
Expected output	0.5100	0.6000
Relative error	0.0253	0.0973

From above the results, it shows that using BP neural network gets the maximum relative error is 0.03106% between training data output value and the sample. The maximum relative error is 0.03106% between respecting data output value and the desired output. We can infer that network self-learning ability and the network performance are good, and also suggests that the comprehensive evaluation method is effective.

CONCLUSION

The problems of third party logistics and supply chain attract the attention of scholars and also have many research results. But collaborative logistics performance indicator system oriented manufacturing and evaluation method are relative lack. This paper makes use of Balanced Scorecard to design the performance evaluation indicator system. And then, it puts forward a kind of model using AHP combined with BP neural network of comprehensive evaluation. Through the collaborative logistics performance evaluation oriented manufacturing automobile of Wen Ling, the model shows that it's reasonable and accurate. From the evaluation results, main research conclusions are as follows.

Firstly, the determination of indicator weight at all levels with the AHP reduces the subjective randomness. From the

evaluation results, financial index weight ratio is 0.3781 and business process index weight ratio is 0.2934. So the two aspects accounts for as high as 0.6715. We can suggest that performance evaluation of logistics should strengthen the investment and application in finance and business processes.

Secondly, when building the BP neural network, it makes use of the adaptive learning rate momentum gradient descent back propagation algorithm-training dx to avoid the local minimum value and improve the stability and efficiency of training model [8].

Thirdly, AHP makes subjective into objective description and enhances the scientific and operation nature of the evaluation results by making through the rational weight assignment to have quantitative processing of large quantities of qualitative index. BP neural network has great adaptive ability and can quickly absorb the knowledge and experience of experts to make more effective and objective evaluation results. Combining the method of AHP and BP neural network, it can provide a new evaluation method for collaborative logistics performance evaluation for manufacturing industry and the test shows that comprehensive evaluation method is effective.

However, collaborative logistics performance evaluation method presented in this paper for the manufacturing industry also has some deficiencies in practice. Firstly, the rationality of established indicator still needs further improvement. Secondly, BP neural network model requires a certain degree of learning samples which have great influence on the learning performance of the neural network model. But selecting the appropriate learning samples is a very difficult and complex. Therefore, aiming at the problems and shortcomings above, it should do further research and improvement work. In spite of this, performance evaluation model based on AHP-BP, easy to operate, provides new research ideas and ways of collaborative logistics performance as the research oriented manufacturing industry.

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