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GA-LMBP Algorithm for Supply Chain Performance Evaluation in the Big Data Environment

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Abstract. An inefficient supply chain (SC) will lead to the resources waste. Big Data as a resource plays a vital role in improving SC performance. Therefore, to evaluate the effectiveness of SC and react the effects of bg data, to find a new evaluation method for SC performance evaluation is important. Firstly, in the traditional environment and Big Data environment, the previous performance evaluation indicator systems and algorithms were reviewed and discussed. Based on this, a five dimensional balanced scorecard was improved and proposed. In the improved five dimensional balanced scorecard, the Big Data usage indicators contained the capacity of gaining value and data leakage degree were proposed. Meanwhile, a method based on levenberg marquardt back propagation neural network algorithm and genetic algorithm was used for SC performance evaluation. Then, based on the practical data of company F, a case study was executed. Results shows that the method proposed has a high convergence speed and a precise prediction ability. The effectiveness and reliability of the model is confirmed. By comparing with the normal back propagation neural network algorithm, results indicates that the model proposed has a higher effectiveness and credibility. This method provides a suitable indicator system and algorithm for enterprises to implement SC performance evaluation in the Big Data environment. In theory, it is a new development of SC performance evaluation theory system and make up for the theory gap on SC performance evaluation. In practically, the method proposed has a theoretical guidance significance for enterprise to implement performance evaluation.

Keywords: big data, genetic algorithm, levenberg marquardt back propagation, performance evaluation, supply chain

1 Introduction

An effective supply chain (hereafter SC) will help company increase their benefits by optimizing resource allocation, decrease transportation cost, etc. An inefficient SC will cause the resources waste and the extra costs. To keep a high SC performance, the SC performance evaluation question is an urgent problem to be solved for corporation. In addition, with the era of big data arriving, Big data are used to improve the performance of supply chain. Therefore, Big Data as a resource have played an important role in SC, the traditional SC performance evaluation should be restructured.

Therefore, the key research problem of this paper is to make some contributions for SC performance evaluation problem in the Big Data environment. Although, many performance evaluation indicators [1-2] and methods [3-7] had been researched, the bionics method of which was viewed as a valid method and could been applied in different areas. Thus, a lot of optimization algorithms from the bionics were discussed. Such as, levenberg marquardt back propagation neural network algorithm (hereafter LMBP

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neural network algorithm) [7], bees algorithm [8], fuzzy neural network [9], genetic algorithm (hereafter GA) [10], ant colony optimization [11]. Among these algorithms, the widely used algorithm was neural network algorithms. Among the neural network algorithms, LMBP neural network algorithm was confirmed to be a valid algorithm for SC performance evaluation [7]. But the algorithm was proved to be easy to sink into a local minimum point. GA as a widely used algorithm for SC performance evaluation has a better global optimum characteristic. Thus, a method combining LMBP neural network algorithm with GA (hereafter GA-LMBP neural network algorithm) was put forward and adopted in many areas [12-15], but its application in SC performance evaluation was a gap. The GA-LMBP neural network algorithm would have a huge potential value and would be used for SC performance evaluation.

For previous indicator systems, 5 dimension balanced scorecard (hereafter 5DBSC) was viewed as the most influential management theory and was thought to be a more exhaustive indicator system. However, it could not react the Big Data usage well. Although a lot of studies had made up this shortage, some limitations still existed: a) some indicators contained in these 5DBSC could not react the impact of Big Data on SC; b) indicators reacting the impact of Big Data on SC were not combined with 5DBSC and could not use for SC performance evaluation. Therefore, revising the 5DBSC to offset the above deficiencies was vital.

To fill the deficiencies of the previous studies, an improved 5DBSC was first proposed. Then, the GA-LMBP neural network algorithm was presented and used based on the improved 5DBSC. Ultimately, a case study was applied to confirm its reliability and validity.

The main merit and achievement of this study was that a new method based on the improved 5DBSC for SC performance evaluation was proposed and used in the Big Data environment. Moreover, the method owned a high scientific value. In practically, the method proposed was implemented based on a case study. By optimizing the performance of SC core enterprise, the purpose that performance evaluation method could guide business practice could achieve. Thereby, the operational efficiency and effectiveness of the SC could be enhanced and SC performance could be enhanced fully. In theory, from a new perspective, a new method for SC performance evaluation was put forward, which was a new development of SC performance evaluation theory system. It not only could accurately assess the level of SC performance, but also could provide solutions to optimize and improve SC performance.

This study was organized as follows: section 1 is introduction; section 2 is methods for SC performance evaluation; section 3 is algorithms for SC performance evaluation; section 4 is the detail content of the improved 5DBSC; section 5 is the related Algorithms of the GA-LMBP neural network algorithm; section 6 is the model of GA-LMBP neural network algorithm; section 7 is a case study; section 8 is conclusions.

2 Methods for SC Performance Evaluation

2.1 In the Traditional Environment

To evaluate the supply chain performance, many efforts have been done and various indicator systems have been proposed and developed. Return on investment as an early method proposed by Dupont Company was widely used [16]. Subsequently, a method included qualitative and quantitative indicators in three areas (resources, output, and flexibility) was presented [17]. Then, SC operations reference was proposed by two firms in USA [18] and was the first global standard SC process evaluation model. In addition, key performance indicator (hereafter KPI) [19] was proposed and adopted for SC performance evaluation. It not only was an instrument to divide a strategic target of a company into an operational target, but also was used in product lifecycle management (hereafter PLM) [20]. Such as, to evaluate the benefits getting through using a PLM tool, a method was disscussed based on KPI [21] and its utility was confirmed by implementing in an Aerospace and Defence firm [21]. In 1992, Kaplan et al. proposed balanced scorecard [22]. In early researches, it included four parts: (1) accounting section, (2) internal business process section, (3) customer section, and (4) learning and development section. The balanced scorecard could learn the excellent experiences from other industries or other firms. Then, it was used as the evaluation standard to assess themselves SC performance, which could help companies catch up or exceed other firms.

Among the above evaluation methods, balanced scorecard was thought to be a more comprehensive and simple method for SC performance evaluation. Moreover, it was thought to be the most influential management theory in recent years. Furthermore, based on an authoritative survey from the Fortune magazine, over 55 percent of the top 1000 companies had applied the balanced scorecard. Company strategy was closely linked with the selection of balanced scorecard indicators. In addition, each style indicator could react a particular angle of the corporative performance.

The models of balanced scorecard were different. From the aspects of cash turnover time, production flexibility, the material flow, and order indicators, it was used in SC performance evaluation [23]. Meanwhile, it had a defect of "cause and effect relationships and time delay, and its variables could be either causes or results and their relationships were not linear" [24]. Furthermore, the performance indicators of suppliers were not included in it. To answer this question, 5DBSC was proposed [25]. It added the supplier performance into balanced scorecard indictor system and made up for the shortcomings of the original balanced scorecard indictor system. 5DBSC had five different sides, and three qualitative and 11 quantitative indicators. However, in the Big Data environment, 5DBSC could not react Big Data very well.

2.2 In the Big Data Environment

With the rapid development of Internet of Things (IoT) and Cloud, global data are increasing rapidly and the era of Big Data has arrived. Russom [26] perspicuously noticed that 70% of the questioned business experts thought of Big Data as an opportunity for business advantage. By using the invisible value of Big Data, the operating margins of retailers could be improved [27]. SC managers were getting more and more dependent on data for evaluating trends in costs and performance [28-29].

However, in the Big Data environment, researches about the performance evaluation indicator system of SC were few. Related researches main focused on He et al. [30], Nie [31], Chen et al. [32], Jin et al. [33], etc. In the study of He et al. [30] and Wu et al. [34], a Big Data analytics method was added and used to evaluate the risk of SC. The methods were proved to be effective. Nie [31] analyzed the competitive advantage that Big Data establishes and presented the retail SC evaluation indicators. In the indicator system, information level indicator contained management information service, Big Data technology, and mobile Internet were proposed to react the impact of Big Data on SC. However, the indicator system proposed was used in the performance evaluation of retailer and the Big Data safety indicators were not included in the system. Recently, Chen et al. [32] proposed the indicators of Big Data security evaluation. It contained data credibility and data privacy protection degree. In addition, there were six indicators (correlation, accuracy, timeliness, integrity, consistency, effectiveness) to react the data credibility and five indictors (the difference degree, variance, entropy, anonymous degree, data leakage risk) to react the data privacy protection degree. However, the data credibility proposed main reacted the credibility of Big Data processing results (i.e., the value of Big Data). Moreover, it could not react the lifecycle of Big Data (data collect, data storage, data mining, and data use [35]). Jin et al. [33] proposed the indicator system of SC partner choice in the Big Data environment. In this indicator system, Big Data processing capacity was chosen to evaluate the usage capability of Big Data. It contained the data decision capacity, data analysis capacity, and data gathering capacity. Although, it contained the ability to obtain the Big Data value, it did not combine with the lifecycle of Big Data well.

Based on the aforementioned analysis, some limitations and findings were got. Limitations: (1) there were not a performance evaluation indicator system based on the lifecycle of Big Data; (2) the indicator systems did not combine with the balanced scorecard; (3) there were not a specialized indicator system for SC performance evaluation in the Big Data environment. Findings: (1) the capacity of gaining value and competitive advantage from Big Data was an important indicator to react the impact of Big Data on SC performance. (2) Big Data security was also a vital indicator for SC in using Big Data effectively.

According to the limitations and findings, it could get that the related indicators of Big Data should contain in the indicator system of 5DBSC for SC performance evaluation in the Big Data environment. Therefore, the indicator system of 5DBSC should be improved. Based on the lifecycle of Big Data, two indicators (the capacity gaining value and Big Data security, in this paper, data leakage degree [32] was used to react Big Data security) were proposed and added in 5DBSC, as shown in Fig. 1 and Table 1.

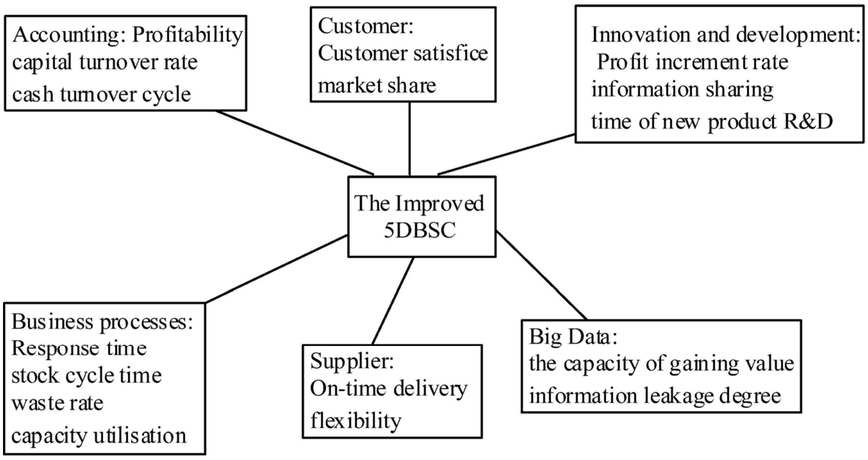

Fig. 1. The indicators of the improved 5DBSC

Table 1. The indicators of the improved 5DBSC

Evaluation dimensions	KPIs	Index Description	Measurement method	Property
Accounting	Profitability (F1)	Profit level of a SC	Net profit / total income (%)	quantitative
	Capital turnover rate (F2)	Management efficiency of the net capital of a SC	Total sales / total value of net assets	quantitative
	Cash turnover time (F3)	Cash flow payback period	Inventory days of supply+ Receivables Age-Payables Age	quantitative
Customer	Customer satisfaction (C1)	Customers' awareness and acceptability	Fuzzy Evaluation	qualitative
	Market share (C2)	Size of the customer community	Product sales / Total sales of industry	quantitative
Business processes	SCRT (SC response time) (P1)	Required time from all enterprises on the chain finding the changes of the market requirements to absorbing these changes and adjusting their plans to meet these changes.	The time required to meet the sudden demand	quantitative
	Stock turnover rate (P2)	Amount of cash in the stock account	Cost of sales / The average occupancy amount of inventory	quantitative
	Waste rate (P3)	The quality control and production technology	number of the Defective products / Total production	quantitative
	Capacity utilization (P4)	Facility application level	Fuzzy Evaluation	qualitative
Innovation and development	Profit increment rate (D1)	Development capability of an enterprise	This period / profit of Previous period	quantitative
	Information sharing (D2)	Level of the information integration Dependent on the partners strategic relationships	Fuzzy Evaluation	qualitative
	Period of a new product R&D (D3)	How fast a chain to response the market changes. Different from each products and enterprises, so it is difficult to determine its value	Statistical Mean	quantitative
Suppliers	On-time delivery rate (S1)	Delivery's capability of a supplier	Punctual delivery times / Total delivery times	quantitative
	Flexibility (S2)	SC's capability of dealing with the special business environment and meeting the customers' special requirements or unexpected requirements.	Fuzzy Evaluation	qualitative
			Recyclable wastes Value / product production gross	quantitative

Table 1. (Continued)

Evaluation dimensions	KPIs	Index Description	Measurement method	Property
Big Data	the capacity of gaining value (B1)	The capacity of SC gain the value form Big Data	Fuzzy Evaluation	qualitative
	data leakage degree (B2)	The degree of data leaked in Big Data collection, storage, mining, and use process, it also contained gaining privacy information from the encrypted data	Fuzzy Evaluation	qualitative

The main contribution was that the capacity gaining value and data leakage degree were proposed based on the lifecycle of Big Data. The capacity gaining value was contained data collection capacity, data storage capacity, data mining capacity, and data use capacity. In addition, information leakage degree contained data collection leakage degree, data storage leakage degree, data mining leakage degree, and data use leakage degree. The lower the leakage degree, the higher the security.

3 Algorithms for SC Performance Evaluation

Although, many methods [3-7] for SC performance evaluation had been discussed, the bionics method of which was thought to be an effective method. It had been adopted by many areas. Thus, a lot of algorithms was proposed to evaluate SC performance. Ant colony optimization algorithm [11] as a probability algorithm had been used to find the optimal route in a chart. In contrast with other algorithms, ant colony algorithm does not need too much the initial path information. However, it has a low convergence and will spend a long time on getting the optimal solution. Bees algorithm [8] was an method by miming bees' behavior to the cluster intelligent thinking. It does not need the special information of issues, which is the main trait of this method. But when the local optimal solution is going to be found, the convergence speed becomes slow. In addition, its disadvantage is easy to get caught in a local optima. Artificial neural network algorithm was an algorithm simulating human thinking and used in many areas [36-38], such as, data mining, decision making, and sequence recognition. Although it has several limitations in SC performance evaluation, many knowledges have developed to support it for SC performance evaluation. GA as a method from imitating the biological evolution law had been widely used to deal with many complicated problems in many areas [10]. Its advantage is to get the global optimal solution easily. However, it is easy to advance convergence.

Among the above algorithms, the widely used method for SC performance evaluation are artificial neural networks algorithm and GA. GA has a good overall optimization nature and is used in many areas. For example, Zhang et al. [39] used it to analyze a SC performance. In addition, it was also used to solve the railway network transport issues [40]. The optimization of GA did not rely on the gradient information. In addition, it could avoid the objective function from falling into the local optimal solution [41].

Artificial neural network algorithm is a method by analyzing the historical data to build a mathematical logic. In contrast the output data with the goal data, it can revise the mathematical logic relationship and get the acceptable error range. In modern artificial neural network models, back propagation neural network algorithm (hereafter BP neural network algorithm) is widely used in SC performance evaluation. For example, Shi et al. [42] used BP neural network algorithm for training and confirmed the similarity between the actual results and the prediction results; Zheng et al. [43] presented a hybrid dynamic method for SC performance evaluation based on BP neural network algorithm. However, BP neural network algorithm has a long computing time. Therefore, many related researches for improving it have been proposed. The widely accepted and used method is LMBP neural network algorithm and it owns an effective training speed. Even though in a larger computation environment, it could play an effective function [7, 44]. In the study of Fan et al. [7], which LMBP neural network algorithm was a better method for SC performance evaluation was proved. The effectiveness of the LMBP neural network algorithm was also proved. However, some limitations are also included in LMBP neural network algorithm. Such as, the optimal solution is easily reach to a local optimization.

Therefore, GA-LMBP neural network algorithm combining GA and LMBP neural network algorithm was proposed. To enhance the accuracy of LMBP neural network algorithm and the search speed and prevent the solutions from falling into the local optima, the advantage natures of GA are used to optimize the initial weights and thresholds of the neural network. Thus, GA-LMBP neural network algorithm appeared. Actually, it has been used in a lot of areas. Such as, prediction of water-assisted injection [12], harmful algal blooms prediction [14], and analog circuit fault diagnosis [13]. Furthermore, it was also used to evaluate the passenger comfort [15], and it confirmed that GA-LMBP neural network algorithm was more effective than normal BP neural network algorithm. However, the application of GA-LMBP neural network algorithm in SC performance evaluation was a gap.

Thus, in this paper, GA-LMBP neural network algorithm would be used to evaluate SC performance. The algorithm not only has the global nature of GA, but also has the local fast convergence natures of LMBP neural network algorithm. GA is adopted for searching and optimizing the initial weights and threshold values of the neural network. The local fast convergence and the network parameters' optimization can use LMBP neural network algorithm. GA-LMBP neural network algorithm can conquer the deficiency of LMBP neural network algorithm (i.e., easy to fall into the local minimum point). Meanwhile, GA-LMBP neural network algorithm can easily get the global solution and has been used in many evaluation problems. However, it is first used for SC performance evaluation.

4 An Improved 5DBSC

Based on the aforementioned researches, the related Big Data indicators were included, it contained the capacity of gaining value and data leakage degree. The capacity of gaining value was contained data collection capacity, data storage capacity, data mining capacity, and data use capacity. In addition, information leakage degree contained data collection leakage degree, data storage leakage degree, data mining leakage degree, and data use leakage degree. Therefore, the improved 5DBSC used to build the performance evaluation model of a SC was showed in Fig. 1 and Table 1.

5 The related Algorithms

5.1 GA

GA is a probabilistic adaptive and iterative optimization process, and it has a good global search. Even though the fitness function is not continuously and unusual, GA can also discover the global optimum point with a high probability. GA does not depend on the gradient information and also has the property of the parallel processing. These properties can be used to optimize the LMBP neural network algorithm.

In GA, the crossover, processes of selection and mutation are three master operations to survival of the fittest. Thus, a suitable method should be chosen for the genetic operation. In this paper, the roulette wheel method is used for the selection operation. The probability that each individual is selected.

$$P_i = \frac{F_i}{\sum_{i=1}^{N} F_i}, \tag{1}$$

In formula (1), F_i expresses the fitness function of individual (i) and N stands for the total number of the individuals for the population. According to P_i, individuals from the population are chosen for the crossover operation.

The arithmetic crossover method is used for the crossover operation and the goal is to generate new individuals. Assume that X_1 and X_2 are the progeny and produced by their parents $X_1^{'}$ and $X_2^{'}$ though the crossover operation. The crossover function is showed in formula (2).

$$\begin{cases} X_1^{'} = aX_1 + (1-a)X_2 \\ X_2^{'} = aX_2 + (1-a)X_1 \end{cases}, \tag{2}$$

Then, to product new individuals, a non-uniform mutation method is used for the mutation operation. Based on the original gene's value, the non-uniform mutation is doing a random disturbance and its results will be as a new gene value after the disturbance. The variance of chromosomes $d(X_i)$ can be obtained by formula (3).

$$d(X_i)=\begin{cases}(b_i-X_i)[r(1-t)]^h & sign=0\\ (X_i-a_i)[r(1-t)]^h & sign=1\end{cases}, \quad (3)$$

In formula (3), b_i and a_i represents the right and left confines and r ($r\in(0,1)$) stands for a random number. $t=g_c/g_m$, g_c expresses the current evolution generation. g_m represents the maximum evolution algebra. Based on these, the new chromosome can be gained, as shown in formula (4).

$$X_i^*=\begin{cases}X_i+d(X_i) & sign=0\\ X_i-d(X_i) & sign=1\end{cases}, \quad (4)$$

X_i has a wide and suitable range. In other words, the search space is great and will become smaller with the increase of t, which can help enhance the accuracy of GA.

5.2 LMBP Neural Network Algorithm

LMBP neural network algorithm combines the gradient descent method and Gauss Newton method. It is a method for optimizing the BP neural network algorithm. Thus, LMBP neural network algorithm has the local convergence of Gauss Newton method and has a better local search ability than the BP neural network algorithm. Assume that s^k stands for the k-th iteration of the threshold value vectors and the network weights. Based on formula (5), the threshold value vectors and the new weights can be gained.

$$\mathrm{s}^{k+1}=s^k+\Delta s, \quad (5)$$

$$MSE(\mathrm{s})=\frac{1}{2}\sum_{i=1}^{N}e_i^2(s)=\frac{1}{2}\sum_{i=1}^{N}(\mathrm{o}_i-d_i)^2, \quad (6)$$

Here, d_i and o_i are the expected output and the output of the network output layer, respectively. The error formula is $MSE(\mathrm{s})$. The formulas (5) and (6) are a single output network, for a multi-output network, the accumulative item of the errors is from m to $m\times n$:

$$\Delta\mathrm{s}=-[J^T(s)J(s)+\mu I]^{-1}J^T(s)e(s), \quad (7)$$

In the formula (7), $e(S)=[e_1(w),e_2(w),...,e_N(w),e_1(\theta),e_2(\theta),...,e_N(\theta)]$. N and I are the total number of the samples and a unit matrix, respectively. The Jacobian matrix is $J(s)$.

6 Model of GA-LMBP Neural Network Algorithm

In the Big Data environment, a model for SC performance evaluation is proposed based on the improved 5DBSC. This model is based on GA-LMBP neural network algorithm, as shown in Fig. 2. This model contains three stages: data preparation is the first stage; obtaining the initialize weights and threshold values of the neural network used GA is the second stage; the third stage is that training the neural network using LMBP neural network algorithm to get the outputs.

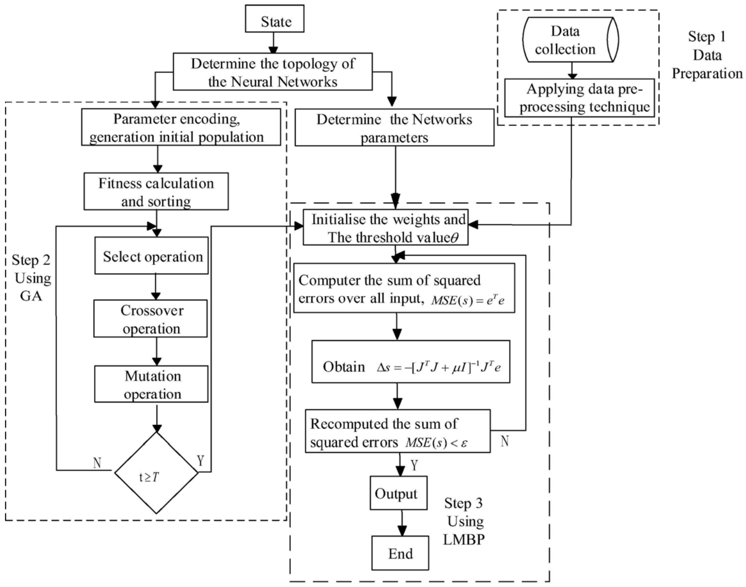

Fig. 2. Procedure of the proposed model

In the first stage, there are two tasks: one is to collect the data of the 16 indicators of the improved 5DBSC, another is the data normalization. In the second stage, the task is to obtain the initialize weights and threshold values of the neural network by using the formulas in section 4.1. In the third stage, the task is to train the neural network using the formulas in section 4.2.

7 Case Study

Matlab was used to apply the model proposed in section 5. An automotive company using Big Data in Chongqing, China was chosen as the case to confirm this model. Considering the privacy questions, the real name of this company is not used. Thus, this company mentioned is called company F. To convey the performance of a SC, a performance indicator system was adopted. Four levels of the performance (poor: P, medium: M, good: G, and excellent: E) were defined. These four levels were represented using 0.25, 0.5, 0.75, 1, respectively, as shown in Table 2. In Table 2, the last column "PE" is the control group data the element and it is adopted for the experimental validations. The data in Table 2 from company F are the original data of the evaluation indicators. Besides the last column, they are all the input data of the model proposed in section 5. The output data of the model is the experimental group data. By comparing the experimental group data with the control group data, the model's validity can be proved. It will be introduced in the following sections.

Table 2. The original data of the SC of Company F in 12 months (2015)

	C_1	C_2	F_1	F_2	F_3	P_1	P_2	P_3	P_4	D_1	D_2	D_3	S_1	S_2	B_1	B_2	PE
Jan.	3	1.59%	0.52	0.328	130	88	0.3	0	4	0.66	3	120	1	3	3	3	G
Feb.	4	1.20%	0.419	0.215	120	92	0.15	0	4	-0.324	4	180	1	4	1	1	P
Mar.	4	1.54%	0.444	0.263	120	90	0.25	0	4	0	3	200	1	2	2	1	M
Apr.	3	1.18%	0.414	0.216	120	92	0.1	0	4	-0.281	4	200	1	4	1	2	P
May	4	1.29%	0.561	0.248	120	90	0.15	0	4	-0.16	4	200	1	4	2	1	M
Jun.	4	1.64%	0.507	0.31	120	89	0.3	0	4	-0.069	4	140	1	3	3	3	G
Jul.	3	1.40%	0.426	0.247	110	90	0.25	0	4	0.157	3	120	1	3	2	2	M
Aug.	4	1.39%	0.459	0.275	110	90	0.25	0	4	0.136	3	130	1	4	3	4	G
Sep.	4	1.64%	0.509	0.322	120	90	0.25	0	4	0.095	4	120	1	4	3	4	E
Oct.	4	1.29%	0.426	0.225	130	91	0.1	0	4	-0.171	3	200	1	3	1	2	P
Nov.	4	1.62%	0.5	0.289	120	88	0.3	0	4	0.489	4	120	1	4	4	4	E
Dec.	3	1.44%	0.468	0.295	110	90	0.2	0	4	0.088	4	130	1	4	3	2	G

7.1 Data Preparation

Data collection. Table 2 enumerated the collected data of the 16 indicators from Company F for 12 months in 2015.

Data pre-processing. In Table 2, the indicators have different dimensions. It should be pre-processed to be dimensionless before inputting into the model proposed in section 5. The dimensionless process is to normalize the indicators' values. It is a procedure to eliminate the impacts of dimensions by the mathematical transformation. The value range of the normalized value should be [0, 1]. In this study, to apply the normal dimensionless process, the linear function normalization is used. Two types of indicators are contained in this system: the cost style and benefit style. For the value of the benefit style, the bigger, the better. In contrast, for the value of the cost style, the smaller, the better. Among these 16 indicators, C_1, C_2, F_1, P_4, D_1, D_2, S_1 and S_2 belong to the benefit style. The others belong to the cost style. $y_i = (x_i - x_{\min})/(x_{\max} - x_{\min})$ is for the benefit indicators and $y_i = (x_{max} - x_i)/(x_{max} - x_{min})$ is for the cost indicators. Here, y_i is the value after normalization and x_i is the original value of the indicators before normalization. x_{min} and x_{max} are the minimum and maximum values, respectively. To determine x_{max} and x_{min}, the 16 indicators should be divided into two kinds: quantitative and qualitative indicators. C_1, P_4, D_2 and S_2 are the qualitative indicators. The others are the quantitative indicators. The qualitative indicators have to be digitized for the further processing. In this paper, 0, 1, 2, 3 and 4 are used to express poor, reasonable, good and excellent performance of these four qualitative indicators. Thus, x_{max} and x_{min} of them are 4 and 0, respectively. For quantitative indicators, x_{max} and x_{min} are determined based on company's experiences. Their values are listed in Table 3. Then, the normalized data are calculated and list in Table 4.

Table 3. The values of $x_{\max}$ and $x_{\min}$ of the quantitative indicators

C_2	F_1	F_2	F_3	P_1	P_2	P_3	D_1	D_3	S_1
(0, 2%)	(0, 1)	(0, 1)	(100,150)	(85,95)	(0,1)	(0,1)	(0,1)	(100,210)	(0,1)

Table 4. The processed data of Company F's SC in 12 months

	C_1	C_2	F_1	F_2	F_3	P_1	P_2	P_3	P_4	D_1	D_2	D_3	S_1	S_2	B_1	B_2	PE
Jan.	0.75	0.80	0.52	0.33	0.4	0.70	0.30	1	1	0.66	0.75	0.75	1	0.75	0.75	0.75	0.75
Feb.	1.00	0.6	0.42	0.22	0.6	0.30	0.15	1	1	-0.32	1.00	0.25	1	1.00	0.25	0.25	0.25
Mar.	1.00	0.77	0.42	0.26	0.6	0.50	0.25	1	1	0.00	0.75	0.08	1	0.50	0.5	0.25	0.50
Apr.	0.75	0.59	0.42	0.22	0.6	0.30	0.10	1	1	-0.28	1.00	0.08	1	1.00	0.25	0.5	0.25
May	1.00	0.65	0.56	0.25	0.6	0.50	0.15	1	1	-0.16	1.00	0.08	1	1.00	0.75	0.75	0.50
Jun.	1.00	0.82	0.51	0.31	0.6	0.60	0.30	1	1	-0.08	1.00	0.58	1	0.75	0.25	0.25	0.75
Jul.	0.75	0.70	0.43	0.25	0.8	0.50	0.25	1	1	0.16	0.75	0.75	1	0.75	0.5	0.5	0.50
Aug.	1.00	0.70	0.46	0.28	0.8	0.50	0.25	1	1	0.14	0.75	0.67	1	1.00	0.75	1	0.75
Sep.	1.00	0.82	0.51	0.32	0.6	0.50	0.25	1	1	0.10	1.00	0.75	1	1.00	0.75	1	1.00
Oct.	1.00	0.54	0.43	0.23	0.4	0.40	0.10	1	1	-0.17	0.75	0.08	1	0.75	0.25	0.5	0.25
Nov.	1.00	0.81	0.50	0.29	0.6	0.70	0.30	1	1	0.49	1.00	0.75	1	1.00	1	1	1.00
Dec.	0.75	0.72	0.47	0.30	0.8	0.50	0.20	1	1	0.09	1.00	0.67	1	1.00	0.75	0.5	0.75

7.2 Chromosomal Gene Coding

The mapping relationships between the weight vectors and the threshold values of each layer and the chromosome code strings are showed in formula (8). In formula (8), every code string represents a special shape of the neural network.

$$[w_{ij}][v_{ki}][\theta_j][\theta_k], \tag{8}$$

In formula (8), the weights between the hidden layer and the input layer are w_{ij}. The weights between the output layer are w_{ki} . $[\theta_j]$ and $[\theta_k]$ are the $j-th$ neuron threshold of the hidden layer and the $k-th$ neuron threshold of the output layer, respectively.

7.3 Fitness Formula

In GA, the fitness function is used to lead to the investigation of the evaluation function and it is not limited by the function's continuity or derivative. For a feedforward neural network, if the energy value of the error formula is small, the network will have a better performance. Thus, the formula (9) is used to stand for the fitness formula.

$$F(\mathrm{x}) = \frac{1}{E(\mathrm{s})}, \tag{9}$$

7.4 Acquisition of the Hidden Layer Nodes

For the multilayer neural network, firstly, the number of the hidden layer should be decided. It has confirmed that the network having at least one linear output layer and one S-type hidden layer can close in any reasonable numbers. The processing capacity of the neural network will raise with the hidden layer number increase. However, the neural network will be more complex. In addition, the training sample numbers and the training time of the network weights are raising. Thus, in this study, a single hidden layer will be adopted. In this neural network, the S-style $\log sig$ function and S-style $\tan sig$ function will be used as the transfer function of the output layer neuron and the hidden layer neuron, respectively.

In the modeling process, it is vital to choose the hidden nodes. If the hidden layer nodes are too little or too much, it will have a passive effects on the neural network. By reviewing a lot of literatures, this article will use a traversal method to decide the number of nodes in the hidden layer. In other words, to get the best hidden layer nodes, the network contains different neurons numbers in the hidden layer will be trained and compared.

Firstly, the node' initial number is set as zero, then adjusting the node number. The corresponding errors of these nodes will be compared. By comparing, it indicates that when the number of the node is 17, the error (4.08E-08) is minimized. Thus, the number of the hidden nodes is 17.

7.5 Application Process

Step 1. It should decide the topology of the neural networks.
Step 2. It should initial the population the algebra t and Pop (N, L). The chromosome gene encode and the fitness formula $F(\mathrm{x})$ should also be given.
Step 3. The fitness formula should be calculated. Then, the corresponding individual of the maximum fitness value should also be reserved.
Step 4. The roulette selection method should be used to do selection operation. The arithmetic crossover should be used to do crossover operation to get the new individuals. The non-uniform mutation should be used to do mutation operation to get the new individuals.
Step 5. Retaining the optimal individual and the new individual. Then, the next generation will take shape.
Step 6. Whether $t \geq T$, if yes, go to step 7. Otherwise, go to step 3.
Step 7. The best individual should be decoded. Then, the decoded value will be used as the initial weights and thresholds of the LMBP neural network. The value of ε and μ should be set.
Step 8. Training the LMBP neural network using the data in Table 4.
Step 9. o_k and $E(s)$ should be calculated. If $E(s) < \varepsilon$, output the result and go to step 10. Otherwise, go to step 8.
Step 10. Output the result, end.

7.6 Results Analysis and Discussion

In Table 4, the last column is the performance value and these values can be showed as

$$d_k = [0.75 \quad 0.25 \quad 0.50 \quad 0.25 \quad 0.50 \quad 0.75 \quad 0.50 \quad 0.75 \quad 1 \quad 0.25 \quad 1 \quad 0.75].$$

Based on the above discussions, in GA, the covariations' coefficient (0.058), the population size (50), the cross coefficient value (0.65), and the evolution (300) are set. The hidden layer (20) and the node number of the input layer (16) is got. The output layer node number is one. The standard MSE is E-02. To confirm the effectiveness of the proposed algorithm, the standard BP neural network algorithm is chosen and compared with the GA-LMBP neural network algorithm.

Through analyzing, based on the data of company F, the results of GA-LMBP network are showed as: when the network of GA-LMBP neural network algorithm reaches the stable state, the value of MSE is 3.12 E-10 and the number of iteration is 8.

Meanwhile, R (the fitness of the network) is approximately 1. The results of the model output is showed as:

$$o_k = [0.7456 \quad 0.2467 \quad 0.5023 \quad 0.2535 \quad 0.5013 \quad 0.7456 \quad 0.5046 \quad 0.7523 \quad 1.0023 \quad 0.2456 \quad 0.9999 \quad 0.7503].$$

Based on the data of company F, the results of the standard BP neural network algorithm are showed as: when the network of the standard BP neural network algorithm reaches the stable state, the MSE value is 5.45 E-4, and the number of the iteration is 25.

Meanwhile, R (the fitness of the network) is 0.85. The results of the model output is showed as:

$$o_k' = [0.7556 \quad 0.2567 \quad 0.5063 \quad 0.2435 \quad 0.4913 \quad 0.7556 \quad 0.4946 \quad 0.7423 \quad 1.0023 \quad 0.2556 \quad 0.9970 \quad 0.7413].$$

dT representes the difference between d_k and o_k. dT' stands for the difference between d_k and o_k'. By analyzing, these results are got.

$$dT = 10^{-2} \times [0.44 \quad 0.33 \quad -0.23 \quad 0.35 \quad 0.13 \quad 0.44 \quad 0.46 \quad 0.23 \quad 0.23 \quad 0.44 \quad 0.01 \quad 0.03],$$

$$E = 10^{-2} \times [0.096 \quad 0.054 \quad 0.026 \quad 0.061 \quad 0.008 \quad 0.096 \quad 0.106 \quad 0.026 \quad 0.026 \quad 0.096 \quad 0.000 \quad 0.001],$$

$$dT' = 10^{-2} \times [-0.44 \quad -0.33 \quad -0.63 \quad 0.65 \quad 0.87 \quad -0.56 \quad 0.64 \quad 0.23 \quad -0.23 \quad -0.56 \quad 0.30 \quad 0.87],$$

$$E' = 10^{-2} \times [0.096 \quad 0.054 \quad 0.198 \quad 0.211 \quad 0.378 \quad 0.157 \quad 0.205 \quad 0.206 \quad 0.206 \quad 0.157 \quad 0.045 \quad 0.378].$$

Based on dT, results that the output of the proposed model with the improved 5DBSC is very similar with the control group data can be got. The maximum error among them is lower than 0.2% and less than 1% accepted in SC performance evaluation. It indicates that the model can be used for SC performance evaluation. In addition, it is accurate, valid and efficient.

From dT', results that the standard BP neural network algorithm with the improved 5DBSC is also accurate for SC performance evaluation can be got. But the maximum error is higher than 0.2%, which shows that the standard BP neural network algorithm using for SC performance evaluation is not so precise in contrast with the model proposed.

Meanwhile, through comparing the iteration number of the proposed model (4) with the standard BP method (20), the proposed model has a lower iteration number. In other words, the proposed model hasa high convergence speed.

8 Conclusions, Significance and Limitations

8.1 Conclusions

In this study, firstly, the existing performance indicator systems and methods for SC performance evaluation were analyzed. The shortages and applications of 5DBSC were analyzed and an improved 5DBSC was proposed. In addition, the shortages and applications of LMBP neural network algorithm, GA, and GA-LMBP neural network algorithm on SC performance evaluation were discussed. Then, a method was proposed. Ultimately, a case was presented based on the new method. Some achievements were got.

An improved 5DBSC for SC performance evaluation were proposed. Based on the analysis on applications and shortages of 5DBSC and the related researches of Big Data usage and evaluation, the 5DBSC for SC performance evaluation was improved. Its main contribution was that the evaluation indicators of Big Data were proposed. The evaluation indicators of Big Data contains the capacity of gaining value and data leakage degree. The indicator modified is more suit to react the usage of Big Data in supply chain.

Namely, a suitable 5DBSC was proposed and the measurement methods of its indicators were more suitable in the Big Data environment. It will provide a reference for building the normal SC performance evaluation indicator system in the Big Data environment.

A new algorithm was used for SC performance evaluation. Based on the applications and shortages of LMBP neural network algorithm, GA, and GA-LMBP neural network algorithm on SC performance evaluation, the GA-LMBP neural network algorithm was proposed and used for SC performance evaluation. Meanwhile, the model of the algorithm proposed was presented. Then, from the aspect of the theoretical analysis and literature analysis, it was proved that the algorithm proposed could be used and help to evaluate SC performance. Meanwhile, it had a high convergence speed and a more accurate prediction ability.

In other words, a new algorithm was used for SC performance evaluation and had a high data processing speed and a more accurate prediction ability. In theory, it is an optimized method and can guide a company's performance evaluation. In addition, it is a new development of SC performance evaluation theory system.

From a practical perspective, the proposed algorithm's effectiveness was confirmed. A case was applied, the practical values of 16 indicators in 2015 were collected from a company F. By using Matlab tool, the proposed model was applied. Results indicates that the proposed model is valid, effective, and reliable. In addition, this model has a faster convergence speed than the normal BP neural network algorithm.

In other words, the proposed model has a practical value in SC performance evaluation. In addition, it has a faster convergence speed and more accurate predictive capability. It can guide business practices well.

8.2 Significance

The method proposed has high scientific significances. In theory, a new method for SC performance evaluation was proposed from a new perspective, which was a new development of SC performance evaluation theory system. SC performance evaluation was implemented through using bionic algorithms. Based on an improved 5DBSC system, the advantages and disadvantages of LMBP neural network algorithm, and the advantages of GA, a new evaluation method was proposed from a new perspective. It not only can accurately assess the level of SC performance, but also can provide solutions to optimize and improve SC performance.

From a practical perspective, the method proposed was implemented based on a case. By optimizing the performance of the SC core enterprise, the purpose that performance evaluation methods can guide business practices can achieve. Thereby, the operational efficiency and effectiveness of the SC can be enhanced and SC performance can be enhanced fully. Therefore, this article has some practical significances in the theoretical innovation and practical applications process.

8.3 Limitations

However, some limitations still exists in this paper. Firstly, it should point out that the model is only based on 12 months' data of company F. To make the model more reliable, more data should be collected to train the network. Meanwhile, the method proposed only is experimented in company F. To prove its reliability, more firms' data should be collected and used.

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