Location Decision of Logistics Distribution Centers Based on Artificial Neural Network

Jinting Nie

ABSTRACT

With the never-ending changes and improvements of science and technology and the rapid development of economy, modern logistics plays an increasingly important role in social and economic development. As an important link between enterprises and consumers, logistics distribution is critical in the smooth development of logistics activities, and the reasonable location of logistics distribution centers is directly related to the distribution efficiency, logistics cost and consumer satisfaction of enterprises. Therefore, this paper studies the location decision of logistics distribution centers, and with the aid of artificial neural network, which can simulate the neural network of human brain and reproduce the process of brain thinking decision, establishes the BP neural network evaluation model, and evaluates the merits and demerits of several location plans with examples. The results show that the method based on artificial neural network is effective and practical and provides a new idea for the location decision of logistics distribution centers.

Key Words: Logistics, Distribution Centers, BP Neural Network, Neuron, Location Problem

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Introduction

With the continuous enhancement of economic globalization, modern logistics has gradually become the "third profit source" of enterprises, which has drawn much more attention from people (Tuğba Efendigil *et al.*, 2008; Ma *et al.*, 2012). In the development of China's economic globalization, logistics economy has become an important element to adjust industrial structure, accelerate economic development and improve economic efficiency.

A logistics distribution center is the place where the enterprise carries out commodity procurement, processing, storage, classification and distribution. The typical operation process of the distribution center is as shown in Figure 1. It can be seen that a distribution center contains almost all the functional elements of the logistics, and it is the epitome and embodiment of the logistics activities and the inevitable outcome of the scale and successful development of the logistics system. In the logistics distribution, it is the first to select the location of distribution centers (Wesolowsky and Love, 2010; Gendreau and Laporte, 2015). The location decision of the distribution center, as its name implies, is the process in which an enterprise selects one or more addresses as distribution centers in a region with several logistics requirements (Ha *et al.*, 2008; Ding and Yu, 2011). The reasonable location decision of the distribution center can bring the best benefit to the whole process of the collection and transportation of the commodities in the distribution center until they reach the consumers (Farahani *et al.*, 2015).

If the location decision of distribution centers is unreasonable, it will have a great negative impact on the enterprise. Therefore, it's

Corresponding author: Jinting Nie
Address: School of Economics & Management, Chang'an University, Xi'an710064, China; Hainan Provincial Department of Transportation, Haikou 570204, China
e-mail✉ hnniejinting@163.com

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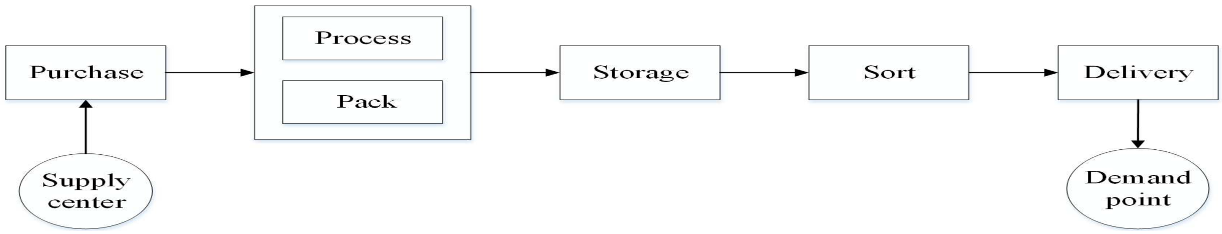

Figure 1. Distribution center operation flow chart

necessary to make a comprehensive analysis from a systematic point of view on the basis of considering the factors affecting the location decision in the process of location decision of distribution centers.

Since the 1980s, with the deepening of the research on modern neurobiology, a new research hotspot in the field of artificial intelligence has gradually emerged - Artificial Neural Network (ANN). This is a network system that can simulate the human brain processing information, which has not only a powerful numerical data processing capability, but also autonomous knowledge learning and memory functions (Rummel and Davis, 1995; Owen and Daskin, 1998), and has been widely used in various fields as a powerful tool to solve all kinds of problems.

Therefore, this paper applies artificial neural network to the location decision of logistics distribution centers, and establishes the location decision model of logistics distribution centers based on artificial neural network. The research conclusion provides a new idea for the location decision of logistics distribution centers.

Introduction of BP Neural Network Model

Network structure

At present, BP neural network or its variation form in artificial neural network is the most widely used model (Jia *et al.*, 2015). Figure 2 is a schematic diagram of a 3-layer BP network with an input layer, an intermediate layer and an output layer. In the same layer, all neurons have no coupling relation and do not influence each other, while in the adjacent layer, there is a complete connection relationship among the neurons. The neuron output signal of the previous layer affects the neuron input and output of the subsequent layer (Philipoom *et al.*, 1997; Colak and Agarwal, 2005). In BP neural network algorithm, there is a division between prediction set and training set (Effati and Pakdaman, 2010; Leshno and Spector, 2015). By setting the error precision between the actual output and the expected output, the threshold value and the weight value of each layer are continuously corrected, so that the actual output is as close as possible to the expected output.

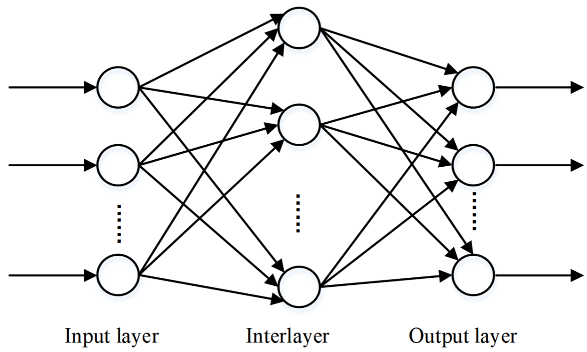

Figure 2. BP neural network structure

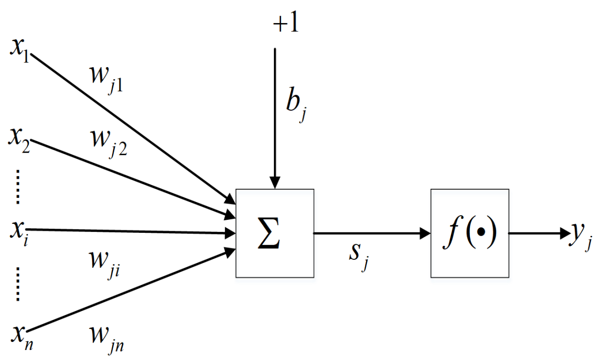

Figure 3. BP neuron structure

In order to imitate the summation, transfer, and weighting functions of biological neurons, the structure of the BP neurons is shown in Figure 3. Assuming there are neurons 1,2,...,n,, $x_1, x_2, ... x_i, ... x_n$ represents the input of neurons, w_{j1}, w_{j2},... 2_{ji},...w_{jn} represents the connection weight between neurons 1,2,...,n and the j^{th} neuron, b_j is threshold value, $f(\bullet)$ is transfer function and then the output y_j of the j^{th} neuron is:

Where, $f(\bullet)$ is monotonically increasing bounded function.

$$y_j = f(\sum_{i=1}^{n} w_{ji} \times x_i) = f(w_j x) \quad (1)$$

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Learning rules

The BP algorithm is a gradient descent method, and its learning rules mainly include normal transfer of information and backward propagation of error as shown in Figure 4 (Yan *et al.*, 2005; Yalcin *et al.*, 2011).

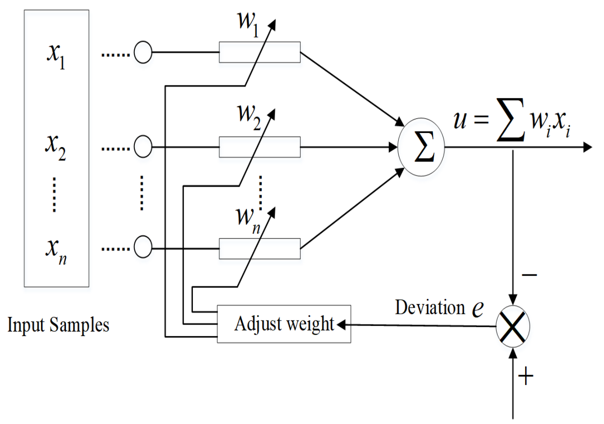

Figure 4. Learning rules of BP neural network

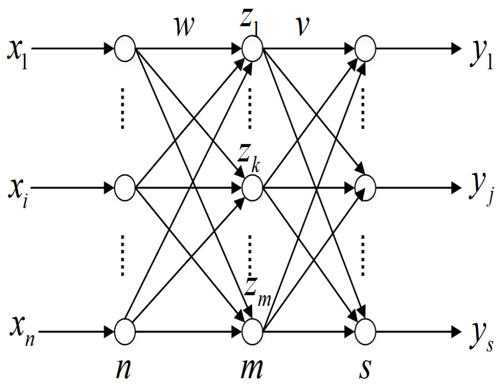

Figure 5. Information forward transfer

The forward transfer process of information is shown in Figure 5. Assuming that the number of nodes in the input, intermediate and output layers of the BP neural network is n,m,s,, the connection weight is w_{ki}, w_{jk}, respectively, and the transfer functions of the intermediate layer and the output layer are $f_1(\cdot), f_2(\cdot)$respectively, then the output of the k^{th} neuron in the intermediate layer is:

$$z_k = f_1(\sum_{i=1}^{n} w_{ki} x_i) \quad k = 1,2,\ldots,m \tag{2}$$

The output of the j^{th} neuron in the output layer is:

$$y_j = f_2(\sum_{k=1}^{m} v_{jk} z_k) \quad j = 1,2,\ldots,s \tag{3}$$

The error function is:

$$E = \frac{1}{2}\sum_{j=1}^{s}(t_j - y_j)^2 \tag{4}$$

In the reverse propagation process, the weight of the k^{th} input of the intermediate layer to the j^{th} output of the output layer changes as follows:

$$\Delta v_{jk} = -\eta \frac{\partial E}{\partial v_{jk}} = -\eta \frac{\partial E}{\partial z_k}\frac{\partial z_k}{\partial v_{jk}} = \eta (t_j - y_j) f_2{}' z_k = \eta \delta_{jk} z_k \tag{5}$$

Where, $\delta_{jk} = (t_j - y_j)f_2' = e_j f_2'$ *and* $e_j = (t_j - y_j)$

The weight of the i^{th} input of the input layer to the k^{th} output of the intermediate layer changes as follows:

$$\Delta w_{ki} = -\eta \frac{\partial E}{\partial w_{ki}} = -\eta \frac{\partial E}{\partial y_j}\frac{\partial y_j}{\partial z_k}\frac{\partial z_k}{\partial w_{ki}} = \eta \sum_{j=1}^{s}(t_j - y_j) f_2{}' v_{jk} f_1{}' x_i = \eta \delta_{ki} x_i \tag{6}$$

Where, $\delta_{jk} = e_k f_1'$ and$e_{k=} \sum_{j=1}^{S} \delta_{jk} v_{jk}$

Modeling training process

Step 1: Randomly input samples

Assume the input samples: $X_k = [x_{k1}, x_{k2}, \ldots, x_{kM}](k = 1,2,\ldots,N)$N is the number of training samples

At the n^{th} iteration, the connection weight of the input layer and the intermediate layer can be expressed as:

$$W_{MI}(n) = \begin{bmatrix} w_{11}(n) & w_{12}(n) & \cdots & w_{1I}(n) \\ w_{21}(n) & w_{11}(n) & \cdots & w_{2I}(n) \\ \vdots & \vdots & \vdots & \vdots \\ w_{M1}(n) & w_{M2}(n) & \cdots & w_{MI}(n) \end{bmatrix}$$

Similarly, at the n^{th} iteration, the connection weight of the intermediate layer *J* and the output layer *P* is *W*$W_{JP}(n)$.

The actual output after the n^{th} iteration:

$$Y_k(n) = [y_{k1}(n), y_{k2}(n), \ldots, y_{kp}(n)](k = 1,2,\ldots,N) \tag{7}$$

The desired output is:

$$d_k = [d_{k1}, d_{k2} ..., d_{kp}] (k = 1, 2, ..., N) \quad (8)$$

Step 2: Initialize
Randomly generate weights for input, intermediate and output layers with smaller random numbers

Step 3: Forward propagation of samples
Forward propagate the samples, and calculate the input and output of each layer

Step 4: Calculate error
Calculate the difference (error) between the actual output and the desired output, judge whether it meets the accuracy requirement, if so, skip to Step 7; otherwise, proceed to the next step

Step 5: Determine the number of iterations
If so, skip to Step 7; otherwise, perform error reverse propagation, and calculate local gradient of neurons of each layer δ

Step 6: Adjust weight
Adjust the weight of each layer according to the correction amount of the weight of each layer

Step 7: End the check
Judge whether all the training samples have been completed, if yes, then end; otherwise skip to Step 3.

Application of BP Neural Network in Location decision of Distribution Center

The nonlinear mapping function of BP neural network from input to output makes BP neural network a powerful tool for solving complex internal mechanism problems (Hamacher and Nickel, 2015). This chapter discusses how to apply BP neural network to the location decision of logistics enterprises, with practical examples to prove the practicability of the method.

BP network structure design

From the above analysis, the BP neural network structure of three layers is designed as shown in Figure 6, in which the input layer is the influence factor of location decision of logistics centers, the intermediate layer is the learning and training process of BP neural network, and the output layer is the comprehensive score of different logistics location plans under each influence factor. The number of nodes in the input layer is the number of influencing factors, the number of nodes in the intermediate layer needs to consider the learning ability and speed of BP neural network, and the number of output nodes is 1.

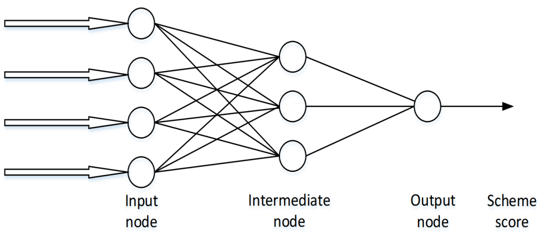

Figure 6. Schematic diagram of BP neural network structure applied to the location decision of distribution centers

Table 1. Factors affecting the location decision of logistics distribution centers

Influencing factors	Environ-mental factors u_1	Weather conditions u_{11}
		Geological conditions u_{12}
		Hydrologic condition u_{13}
		Tax stability u_{14}
		Stability of political policy u_{15}
	Economic Factors u_2	Fixed cost u_{21}
		Variable cost u_{22}
		Transportation cost u_{23}
		Availability of labor resources u_{24}
		Availability of land resources u_{25}
	Traffic factors u_3	The degree of connection with the highway network u_{31}
		The degree of connection with the railway network u_{32}
		The degree of connection with the port u_{33}
		The degree of connection with the airport u_{34}
		Degree of connection with urban traffic u_{35}

689

Table 2. Data of each index of logistics distribution centers of an enterprise over the years

	u_{11}	u_{12}	u_{13}	u_{14}	u_{15}	u_{21}	u_{22}	u_{23}	u_{24}	u_{25}	u_{31}	u_{32}	u_{33}	u_{34}	u_{35}	Expert value
1	0.73	0.89	0.79	0.81	0.75	0.71	0.72	0.72	0.71	0.75	0.73	0.72	0.75	0.82	0.77	0.7482
2	0.71	0.89	0.80	0.79	0.71	0.65	0.71	0.72	0.65	0.67	0.73	0.72	0.72	0.77	0.75	0.7249
3	0.74	0.85	0.82	0.85	0.75	0.73	0.77	0.75	0.72	0.74	0.75	0.72	0.79	0.82	0.81	0.7593
4	0.75	0.87	0.72	0.82	0.83	0.75	0.76	0.77	0.72	0.75	0.77	0.72	0.79	0.81	0.80	0.7297
5	0.72	0.71	0.69	0.72	0.65	0.63	0.62	0.72	0.60	0.72	0.65	0.62	0.69	0.71	0.72	0.6621
6	0.71	0.72	0.65	0.71	0.67	0.61	0.60	0.70	0.60	0.71	0.65	0.62	0.70	0.71	0.70	0.6448
7	0.88	0.89	0.92	0.89	0.90	0.91	0.91	0.88	0.89	0.92	0.89	0.90	0.91	0.91	0.90	0.9000
8	0.72	0.71	0.71	0.65	0.72	0.65	0.62	0.67	0.72	0.67	0.65	0.72	0.66	0.71	0.65	0.6892

Table 3. Result output of different alternatives

	u_{11}	u_{12}	u_{13}	u_{14}	u_{15}	u_{21}	u_{22}	u_{23}	u_{24}	u_{25}	u_{31}	u_{32}	u_{33}	u_{34}	u_{35}	Training results
1	0.12	0.61	0.65	0.59	0.78	0.56	0.56	0.53	0.61	0.70	0.59	0.65	0.61	0.69	0.62	0.5801
2	0.75	0.82	0.76	0.80	0.72	0.66	0.72	0.70	0.65	0.72	0.71	0.70	0.75	0.75	0.72	0.7267
3	0.87	0.91	0.85	0.86	0.83	0.83	0.85	0.85	0.85	0.87	0.85	0.87	0.86	0.85	0.84	0.8613
4	0.61	0.71	0.71	0.65	0.65	0.63	0.67	0.71	0.71	0.60	0.65	0.69	0.77	0.67	0.61	0.6498

There are many factors affecting the location decision of logistics distribution centers, including macro and micro factors, as well as qualitative and quantitative factors. According to the actual situation, the factors affecting the location decision of logistics distribution centers are divided into environmental, economic and traffic factors, and the specific indexes under each factor are shown in Table 1. The data of each index of logistics distribution centers of an enterprise collected over the years are shown in Table 2.

Training and results of BP neural network

The data in Table 2 are normalized as training samples, and BP neural network training is carried out by using Matlab neural network toolbox. Select $\log sig$ function as processing function, adopt *mean squared error*function as error and use*Traingda (Gradient descent with adaptive lr backpropagation)* as training function to form BP neural network.

The number of nodes in the intermediate layer needs to consider the learning ability and speed of BP neural network. Referring to the previous experience, this paper selects the number of nodes in the intermediate layer as:

$$n=\sqrt{n_i+n_0}+a$$
(9)

Where, n_i, n_0 represent the number of nodes in the input and output layers, respectively and a is a constant between 1~10.

The pre-selected plan index data of the four distribution centers are input into the BP network for processing, the error output is shown in Figure 7, and the result output of the different alternatives is shown in Table 3.

As can be seen from Table 3, Plan 3 is the best and Plan 1 is the worst. Therefore, according to this table, the optimal logistics distribution center can be determined as Plan 3.

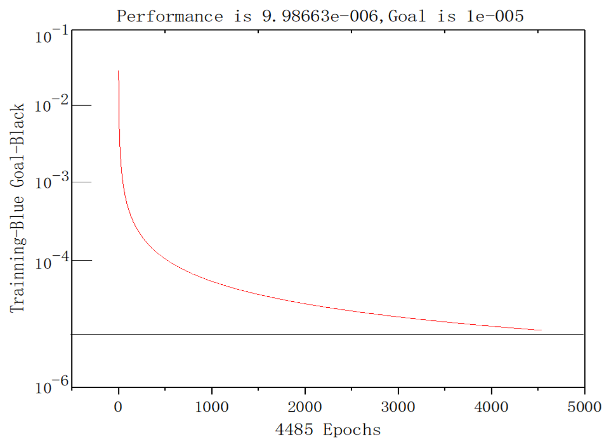

Figure 7. Error output

Model evaluation

Applying BP neural network to the location decision of logistics distribution centers has the following two advantages:

(1) In view of BP neural network's characteristics of data parallel processing, many factors affecting the location decision of logistics distribution centers can be considered comprehensively. At the same time, through the adaptive function of BP network, the model can perform autonomous learning and training to find out the internal relation between the input information and the output result, so as to solve the problem. This method is not based on empirical knowledge, so it can weaken the influence of human factors in index weight, and has more advantageous than the general fuzzy

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evaluation method.

(2) Because of the mutual influence of the factors influencing the location decision of distribution centers and the complicated linear relation, it is very difficult to evaluate different plans on location decision of distribution centers in practice. The powerful function of BP neural network makes it gradually become a powerful tool in dealing with this kind of problem.

Therefore, if some historical data have been accumulated in the location decision of logistics distribution centers, the decision evaluation method based on BP neural network has great superiority compared with other evaluation methods. Although the BP neural network algorithm is similar to the "black box" operation, it has been proved that by virtue of its powerful learning and training ability, it can comprehensively consider multi-factors and finally output a more accurate prediction value on location decision of distribution centers after nonlinear transformation.

Conclusions

The location decision of logistics distribution centers is an important link in logistics system planning. Its merits and demerits play an important role in the healthy growth of enterprises and thus it is necessary to enhance the accuracy, scientificity and practicality of the location decision. Therefore, this paper abandons the former "experience form" and "chest thumping, taking it for granted", and apply the artificial neural network to the location decision of distribution centers. The research conclusions are as follows:

(1) There are many factors affecting the location decision of logistics distribution centers, which need to be considered comprehensively, not only from the perspective of enterprise economy, but also from the perspective of environmental friendship for social sustainable development.

(2) Artificial neural network (ANN) abstracts the neural network of human brain from the angle of information processing, and can simulate the function of brain nerve in memorizing and processing information. Therefore, the location decision of logistics distribution centers based on artificial neural network, compared with the general fuzzy evaluation method, can more objectively carry on the comprehensive evaluation to multiple location plans, and the example also proves that the method has the better effect.

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