Proportionality of component factors in shipping safety cost based on GA-BP model

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Abstract

Security is the base of development. Shipping safety is of great significance in promoting rapid and sound development of shipping economy, and the efficient investment of shipping safety cost is the guarantee of the increase of shipping safety economic benefit and shipping security level. Shipping safety cost consists of the guarantee-purpose safety cost and the cost of safety failure. It is found that the guarantee-purpose shipping safety cost composition also influences the cost of shipping safety failure, and the relationship between them is complex nonlinear. The component factors of shipping safety cost are discussed from the perspective of shipping business actual. Genetic algorithm is adopted to optimize neural network, which improves the convergence rate and precision of neural network. The genetic algorithm optimizing neural network model (GA-BP) is established to quantify the proportionality between the guarantee-purpose shipping safety cost composition and the cost of shipping safety failure through network training. This research provides data support for the effective investment decision of shipping safety cost.

Keywords: Guarantee-purpose Safety Cost, Cost of Safety Failure, Input-Output, Genetic Algorithm, Neural Network

1 Introduction

Shipping industry should create benefits as the pillar of economy, but it also should avoid the effect of inverted funnel formed by the financial loss. Therefore, it's important to be aware how to input the safety cost, which makes the safety cost and financial loss perfectly balance. The researches of safety cost focus on coal, Electric power, railway and construction industry, but the research on shipping safety cost has been still bank recently in China [1,2]. Just grey relational analysis has been used in researches on the effect of component factors of shipping safety cost on system security now. This method can only rank the influence of each component factor on the system security or loss, which is helpful to adjust the input of the safety cost of every item reasonably [3,4]. However, the extent of effect has not quantified. This research quantifies the effect of safety cost input to accident or risk loss.

2 The concept and component of shipping safety cost

2.1 THE CONCEPT OF SHIPPING SAFETY COST

The economic significance of shipping safety cost is that it reflects synthetically all the costs to achieve the shipping security goals. Its manifestation is the sum of all costs associated with shipping security[5]. So the shipping safety cost can be defined as the followings: it is all expenses of the shipping safety management, shipping safety training and the loss caused by shipping accidents to ensure the shipping safety, raise the level of shipping security, prevent shipping accidents, eliminate the shipping security risks, avoid or reduce casualties and economic loss for shipping enterprise and shipping administrative department [6].

2.2 THE COMPONENT OF SHIPPING SAFETY COST

With reference to researches of safety experts and safety organizations (International Labour Organization) both in China and abroad, shipping safety cost can be divided into two parts: guaranteed shipping safety cost and cost of shipping safety failure.

2.2.1 Guaranteed shipping safety cost.

Guaranteed shipping safety cost refers to the total planning and preventive cost in shipping safety management that shipping enterprise and shipping administrative department expend to ensure the safety during production.

Combined with the connotation of shipping safety cost and the characteristic of joint management between enterprise and government, the component factors of guaranteed shipping safety cost can be designated as following: engineering cost of shipping safety management, shipping safety facilities fee, environmental safety and health measures cost, cost of security inspection and overhaul, safety technology cost, education and publicity expense, and labour production fees.

2.2.2 Cost of shipping safety failure.

The cost of shipping safety failure refers that potential safety hazard of shipping enterprise in the production process influences regular production and operation (or the bad condition of safety system can't meet shipping enterprise normal work), and the safety problem lead to loss as a result of accidents.

There are two indicators used for evaluating maritime safety accident loss in China. One is the direct economic loss (includes the cost of treatment for injured people and the pension for dead family members), the other is the

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number of dead or missing. Therefore, the direct economic loss and the case of dead/missing could be selected as component factors of cost of shipping safety failure. In the shipping safety accident statistics, the direct economic loss has quantified as money value. The case of dead/missing can be quantified according to social labor value loss caused by dead or missing mariners. Based on the per Capita GDP of annual shipping personnel and the economic growth rate, the social labor loss can be easily calculated. The per capital economic loss of dead or missing people in the shipping accidents are valued as shown in Table 1.

TABLE 1 Present value of Social labor loss per capita economic loss caused by dead or missing in maritime accident

Age group		21-25	26-30	31-35	36-40	41-45	46-50
Value (yuan)	Before 2010	356410	356412	356431	356441	356472	356508
	After 2010	554414	53338	508086	477634	440988	396883

3 Analysis of relationship between guaranteed shipping safety cost and cost of shipping safety failure

There is a simple input-output relationship between guaranteed shipping safety cost and cost of shipping safety failure. Furthermore, it is proposed that different constitution of guaranteed shipping safety cost input has a different influence on shipping system safety while total guaranteed shipping safety cost is under a certain condition. In other words, if the input of shipping safety cost constitution is different, the loss will be different, too.

3.1 SELECTION OF INDICATOR

Input and output analysis is the combination of economic analysis and mathematical analysis, which is used for the study of economic relationships. On the basis of existing research, this paper doesn't simply study the shipping safety cost input-output relationship, but adopts a further refinement. Two indicators is suggested in the analysis: "guaranteed safety cost"- "Y" and "cost of shipping safety failure" – "Z". Y consists of 7 sub-indicators:

$Y=\{y_1,y_2,y_3,y_4,y_5,y_6,y_7\}$,

y_1 is "engineering cost of shipping safety management"; y_2 is "shipping safety facilities fee"; y_3 is "environmental safety and health measures cost"; y_4 is "cost of security inspection and overhaul"; y_5 is "safety technology cost"; y_6 is "education and publicity expense"; and y_7 is "labor production fee". Z has two sub-indicators, $Z=\{z_1,z_2\}$. z_1 is direct economic loss; and z_2 is number of dead or missing.

During the indicators: y_1~y_7 and z_1 are direct money value; z_2 can be transformed into money value at current year according to Table 1. The economic value analysis of shipping safety cost input and output is conducted on the basis of dimensional normalization. Then, input indicators of guaranteed shipping safety cost are y_1~y_7; output indicators are total cost of shipping safety failure z_0, $z_0= z_1+z_2$.

3.2 SELECTION OF SHIPPING SAFETY COST INPUT – OUTPUT BASIC MODEL

Although shipping safety accident consequence is affected by many factors, there is still a certain connection between these factors and safety cost input. Therefore, it is supposed that the relationship between safety cost and accident loss is multi-layered nonlinear. For shipping safety cost input-output system, corresponding data of guaranteed safety cost input and loss output could be collected, but there is no inherent mathematical model to describe the relationship between guaranteed shipping safety cost input and cost of shipping safety failure. However, neural network model provides a good solution.

Neural network model is developed from mindlike machine to learning machine. Neural network constituted by simple neurons is used for simulating the capacity of learning, memory, calculation and processing. It could conduct arithmetic learning and data processing of nonlinear dynamic systems that refer to many factors and multilayer. The neural network model can study the mapping relationship between guaranteed shipping safety cost input and the cost of shipping safety failure output according to network training with its capability of self-learning, adapting, organizing, and massive parallel distributed processing. Under the circumstance that network training result has the highest fitting degree with output target, the best nonlinear mapping relationship can be got, which is the shipping safety cost input-output model.

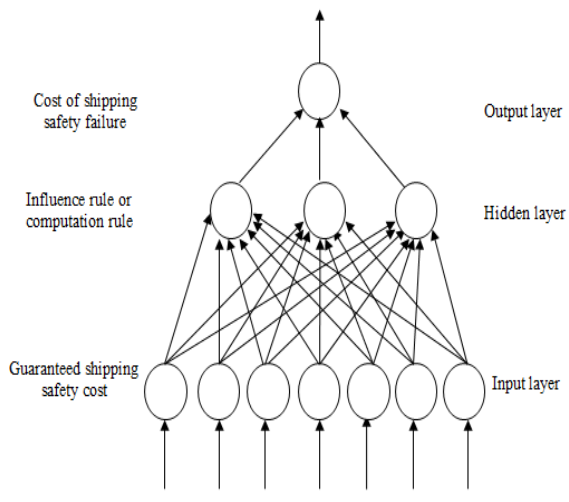

FIGURE 1 Shipping safety cost input-output neural network topological graph

Neural network model is built by nonlinear mapping relation between the input of m dimensional space and the output of n dimensional space. Based on the fully trained neural network model, input the general expenses of guaranteed shipping safety cost, then the output can be calculated. The input is a seven-dimensional vector and the output is one-dimensional variable. Firstly, parallel structure and Parallel implementation capacity of neural network model is reliable, which means it is of strong adaptive ability handling Failure. Even if abnormal data exits in network building, the model could handle properly. That is, the neural network model permits the existence of abnormal data. So the final model's structure and rule are more reasonable. What's more, neural network is trained by recording data. As the degree of fitting is the most accurate, the model has the ability to conclude characteristics of all data. It could be universally applied, and there is no need to take other forecast methods into consideration. The neural network topological of shipping safety cost input and output is showed as Figure 1, in which a good topological relation between shipping safety cost and neural network exists. So the neural network model can provide technical support for shipping safety cost input-output model.

According to the neural network topology, the shipping safety cost input-output neural network model can be described as the followings: put the composition of guaranteed shipping safety cost as input vector, and the vector is a seven-dimensional vector; put the sum value of direct economic loss and dead/missing loss as the output vector, and the vector is a one-dimension vector.

Carry out neural network training and adaptive learning with the recent data as the network training sample data. The weight coefficient and threshold value can be easily got. The input-output nonlinear mapping relation is the correct representation of internal model arithmetic. The trend of neural network training is converging to the minimum global network error. The final model can be obtained by the training, mainly through the error indicator function, as shown in Equation (1).

$$E\left(w\right)=\frac{1}{2}\sum_{p}\sum_{k}(t_{pk}-o_{pk})^{2}. \tag{1}$$

In Equation (1), t_{pk} is the given output value from the statistical data, o_{pk} is got from the network model, p is the number of training sample, k is the dimension of output vector.

With the view of adjusting weight coefficient value by continual learning, network training decrease the system error to achieve the highest fitting degree of network. With the steepest descent method, the weight value learning can be described as Equation (2) and (3).

$$\Delta_p w_{kj}=\eta\delta_{pk}o_{pj}\ , \tag{2}$$

$$\Delta_p w_{ji}=\eta\delta_{pj}o_{pj}\ . \tag{3}$$

In Equation (2) and (3) ,

$$\delta_{pk}=(t_{pk}-o_{pk})o_{pk}(1-o_{pk}),$$

$$\delta_{pj}=o_{pj}(1-o_{pk})\sum_{k}(\delta_{pk}w_{kj}),$$

where η is the learning step size.

3.3 ESTABLISHMENT OF THE MODEL BASED ON GENETIC ALGORITHM OPTIMIZING NEURAL NETWORK (GA-BP)

The final model of neural network is based on the network that can make the global error to the minimum after the training.

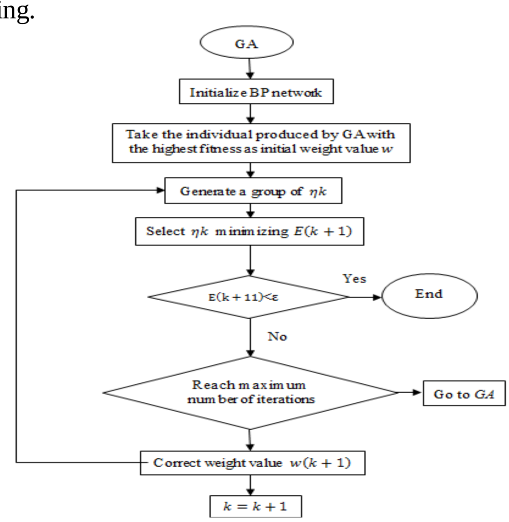

FIGURE 2 Establishment of neural network model based on genetic algorithm

In the process of network optimization to confirm the best weight value, it plays a crucial role in the convergent speed and precision to choose the learning step size. Reasonable step size can make the number of network training; convergent speed and network precision reach a higher level. the number of training may be more and can easily converge into local minimum point while the step size is small, the convergent speed is slow; on the contrary, while the step size is too big, it would be fail to obtain network model of high fitting precision because of the divergence or shock in the optimization process. But above all, in the small-step learning process, although the convergent speed is slow, the optimal solution is of high accuracy. What's more, genetic algorithm searches from the multipoint group, which has the implicit parallelism, high adaptability, high robustness and computational efficiency. In spite of its poor convergence, the global optimization speed of genetic algorithm (GA) is fast. Combining GA with neural network – genetic algorithm optimizing neural network (GA-BP), can overcome the problem, and GA-BP can also improve the convergence speed of neural network [7]. The specific combination is shown in Figure 2.

The key point of GA-BP model is how to optimize the neural network with genetic algorithmic. Genetic algorithmic mainly optimizes weight value of genetic network to improve convergence efficiency [8]. Specific optimization steps are as follows.

1) Confirm the parameter and code in the genetic algorithmic to optimize

The training of neural network aims at adjusting weight value through continual learning, making the system error decrease to reach the highest degree of fitting. So the parameter to be optimized is weight value and threshold value of neural network node. The processing object of genetic algorithm is character string, so use 8-bit binary to code. Confirm the optimizing parameter and its own variation range, and use unsigned binary number to describe it. For example, assume that one certain parameter's variation range is from x_{min} to x_{max}, if describe it by using *m*-bit binary y, then $y = (2m-1)(x - x_{min}) / (x_{max} - x_{min})$.

Make the sample as binary character string s that is cascaded with all the binary number of optimizing parameter. If they are coded as *m*-bite binary number and the total number is r, then the digit is $m \times r$.

2) Initialize population

Confirm the parameter in the genetic algorithm such as the probability of population cross or variation. In the neural network based on the genetic algorithm, the individual is the network weight threshold value. The initial number in the initial population is random, ranging from x_{min} to x_{max}, and the genetic value is uniformly distributed random numbers in the same range. The generation of initial population not only improves the searching speed but also expands the searching range of feasible solution. The selection of parameter N generates N initial populations, which means that individual is the possible solution in optimization problem. When the individual generates randomly, there is a random number between 0 and 1. Compared with the permissible error, if the number is less than 0.5, then reset; or if the number is greater than 0.5, the location of the chromosome is 1. The random initial individual is got unless the location of the chromosome is 0 or 1 all the time.

3) Decode the chromosome

As all the chromosomes are the binary string, it is necessary to decode while judging whether the individual achieves the best optimization. If the corresponding array element of weight value w_{ij} is positive integer U_{ij}, then use Equation (4) to describe the mapping relation.

$$w_{ij} = \left(w_{ij}\right)_{min} + \frac{U_{ij}}{2^b - 1}\left[\left(w_{ij}\right)_{max} - \left(w_{ij}\right)_{min}\right], \qquad (4)$$

$(w_{ij})_{max}$ is the maximum of neural network weight value, $(w_{ij})_{min}$ is the minimum of neural network weight value, b is the binary bite, b =8.

The decoding process is: firstly give the integer variable i value 0, calculate $chrom[i]$ and then give it to U, then use Equation (4) to get the corresponding weight value. Secondly, make $i = i + 1$, calculate the weight value until all the value can be obtained.

4) Calculate the value of fitness function

The calculation is the joint point with genetic algorithm and neural network model. Evaluate the superior degree of population individual through genetic algorithm, and its evaluation criteria are the fitness function value. The individual ability to adapt environment reflects the function directly. The higher the fitness value is, the more accurate the corresponding node weight value is, and the more suitable for neural network training and fitting is.

The fitness function corresponds to optimized indicator function, aiming at finding out each optimization parameter of the sample and calculates its fitness value, then arranges them according to the order. Besides, it is necessary to transform it at different stages in line with individual fitness value. Linear dimension variation method is selected to adjust it.

5) Genetic operation

Optimize the weight value and threshold value of neural network node by selecting operator, crossover operator and mutation operator.

<u>(1) Selecting operation</u>

Make the population scale as G, and then the individual with degree of fitness f_i is selected into the next generation probability calculation, shown as Equation (5):

$$P_i = f_i / \sum_{i=1}^{G} f_i = f_i / f_{sum} \ . \qquad (5)$$

In Equation (5), P_i is the selection probability of individual i, f_i is the fitness degree of i, f_{sum} is the total fitness degree of population[9].

<u>(2) Crossover operation</u>

Calculate the crossover probability with adaptive adjustment algorithm. Exchange a part of gene to generate offspring. the calculation is shown as Equation (6):

$$P_c = \begin{cases} k_1 (f_{max} - f_c') / (f_{max} - \bar{f}), & f_c' \ge \bar{f} \\ k_2 , & f_c' < \bar{f} \end{cases}, \qquad (6)$$

f_c' is the larger fitness function value among the parent parents before crossover[10].

6) Add the new individuals that are children samples, into the original sample or the sample that are original excellent parent of the last generation, to form a new generation. Then the genetic manipulation has been accomplished. Take advantage of corresponding optimized vector to calculate fitted value, and conduct a new iteration until the satisfying fitted value is found out. At last, select the best sample and decode its character string to obtain optimal parameter.

7) Optimize weight value and threshold value of neural network with genetic algorithm, then build neural network model based on the genetic algorithm (GA-BP) through network training [11,12].

4 Analysis of equilibrium relationship between guaranteed shipping safety cost and cost of shipping safety failure

The analysis of the equilibrium model aims at finding out the equilibrium relationship, and ascertains the output (cost of shipping safety failure) under different input strategies of guaranteed shipping safety cost. Since the algorithm model has been established to confirm the relation, it's necessary to modelling and demonstration based on the current data.

4.1 OPTIMIZED NEURAL NETWORK MODEL VECTOR BASED ON GENETIC ALGORITHM

The three-layer network structure of equilibrium relationship has been confirmed according to the previous research. In order to make the approximation accuracy and the fitted degree higher, the hidden node number of interlayer is 25 from experience [13].

According to the calculation and analysis for the confirmed neural network, if the rate of convergence is needed to be fast, the value of learning efficiency and impulse divisor should be larger, which is good for network training. So assign value 1 to learning efficiency "η", value 0.5 to impulse divisor "α", value 50 to iterations, value 0.0001 to network training accuracy "ε", value 0.05 to the original learning rate. Its adjustment rule is shown as Equation (7).

$$\alpha(N+1)=\begin{cases}1.2\alpha(N), E(N+1)<E(N)\\ 0.7\alpha(N), E(N+1)>1.1E(N)\\ \alpha(N), E(N)\le E(N+1)\le 1.1E(N)\end{cases} . \quad (7)$$

The weight value and threshold value of node in the network is the random number between -1 and 1[14]. The constitution of guaranteed shipping safety cost is used as the input and the cost of shipping safety failure is used as output of GA-BP model in this paper. Owing to highly economic values of high discretization, it's easy to result in low rate of convergence and violent shake in network training. It's better to lead the normalization into model building. Normalize the actual input and output, and then inverse normalization to obtain the output. Since the relationship between input and output is complicated and non-linear, the excitation function of interlayer- sigmoid function is also non-linear generalized function. Its expression is $y=1/\left(1+e^{-\lambda x}\right)$, λ is the constant.

4.2 SAMPLE SELECTION AND DATA PROCESSING

On the basis of current research, combined with the existing approach to obtain data and consider the objectivity, reliability and the number of sample. This paper makes the X shipping company in Q strait as the carrier, and consults financial data of company and supervision department within area, gathers 14 shipping safety accidents/dangerous cases in recent 5 years as research samples. According to current shipping accidents, it's ordinary to adopt direct financial loss and dead/missing people as statistics, which are the original data. Firstly, quantify the casualties condition into financial loss, the learning sample is shown in Table 2.

Since it is important to increase the comparability of training sample and eliminate influence caused by the large discrepancy among values on training accuracy and results, it is necessary to normalize learning sample data to ensure the nonlinearity of network neurons. First, normalize the sample by calling premnmx function. Then convert the data to the numerical value in the interval [-1,1], as shown in Equation (8):

$$y=\left(y_{\max}-y_{\min}\right)\times\left(x-x_{\min}\right)/\left(x_{\max}-x_{\min}\right)+y_{\min}, \quad (8)$$

y is the data after normalization;

$x_{\max}$ is the largest numerical quantities before normalization;

$x_{\min}$ is the smallest numerical quantities before normalization;

$y_{\max}=1$, $y_{\min}=-1$.

The results of all the input and output samples are shown in Table 3.

TABLE 2 Learning sample of GA-BP model

Monetary unit: *yuan*

Sample \ Indicator	y_1	y_2	y_3	y_4	y_5	y_6	y_7	z_0
1	53234	3600018	2077	16451	79037	109854	708272	300000
2	86312	3388888	2142	16535	79313	113930	742354	150000
3	86312	3388888	2142	16535	79313	113930	742354	400000
4	162952	4555892	2387	31699	93903	148919	850139	400000
5	162952	4555892	2387	31699	93903	148919	850139	150000
6	172536	4667203	3202	75816	91536	168747	1373625	5575000
7	140553	4221166	3175	47980	56674	235977	1287278	10000
8	162952	4555892	2387	31699	93903	148919	850139	120000
9	137535	18974286	23202	141970	94196	227556	1729584	149000
10	172536	4667203	3202	75816	91536	168747	1373625	3485700
11	137535	18974286	23202	141970	94196	227556	1729584	2952000
12	303808	19050758	23202	1531998	78138	214175	2504640	300000
13	56312	3388888	2142	16535	79313	113930	7423541	160000
14	194613	12052466	25522	143674	94666	224121	1729584	100000

TABLE 3 Sample normalization of GA-BP model

Indicator / Sample	y_1	y_2	y_3	y_4	y_5	y_6	y_7	z_0
1	-0.74	-1	-0.99	-1	0.19	-0.94	-0.96	-0.9
2	-0.74	-1	-0.99	-1	0.19	-0.94	-0.96	-0.95
3	-0.12	-0.85	-0.97	-0.98	0.96	-0.38	-0.84	-0.86
4	-0.12	-0.85	-0.97	-0.98	0.96	-0.38	-0.84	-0.86
5	-0.05	-0.84	-0.9	-0.92	0.84	-0.07	-0.26	-0.95
6	-0.3	-0.89	-0.91	-0.96	-1	1	-0.36	1
7	-0.12	-0.85	-0.97	-0.98	0.96	-0.38	-0.84	-1
8	-0.33	0.99	0.8	-0.83	0.98	0.87	0.14	-0.96
9	-0.05	-0.84	-0.9	-0.92	0.84	-0.07	-0.26	-0.95
10	-0.33	0.99	0.8	-0.83	0.98	0.87	0.14	0.25
11	1	1	0.8	1	0.13	0.65	1	0.06
12	-0.98	-1	-0.99	-1	0.19	-0.94	-0.96	-0.9
13	0.13	0.11	1	-0.83	1	0.81	0.14	-0.95
14	-0.74	-1	-0.99	-1	0.19	-0.94	-0.96	-0.97

4.3 CONSTRUCTION, SIMULATION AND EMPIRICAL RESEARCH

The model that has been built is multilayer neural network. The hidden layer has 25 nodes; input layer has 7 nodes; output layer has 1 node; and encoding length of genetic algorithm is 7×25+25×1+25+1=226. The individual in the algorithm corresponds to network threshold value, and it has been normalized into a random number. Values are between -1 and 1. What's more, the initial value generated by original population is also a random number, and its value is between -1 and 1. So the input data and the individual in algorithm are consistent with each other. It can improve searching speed, expand the range to find out feasible solution, and also increase the rate of convergence. Assign value 50 to population size. These 50 individuals correspond to a neural network that has different weight value but same structure. So the basic parameters are: encoding length of genetic algorithm is 226; population size is 50; the value of genetic number is in the interval [-1,1]; training speed is 1; iterations is at 50 times.

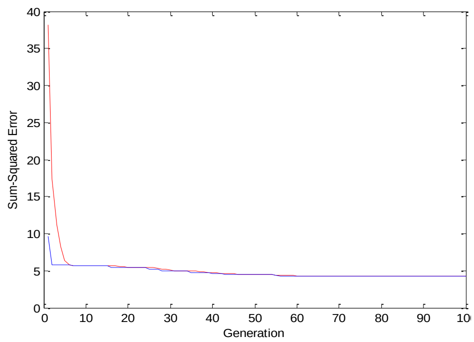

FIGURE 3 Population generation and network error

The algorithm is accomplished by Matlab software. The population generation and error relation is shown in Figure 3.

According to the figure, when the population reaches 60 generations, the error declines to the lowest and tends to be smooth. On the other hand, when population reaches 70 generations, the fitness degree level is the highest. The relationship between population generation and fitness is shown in Figure 4.

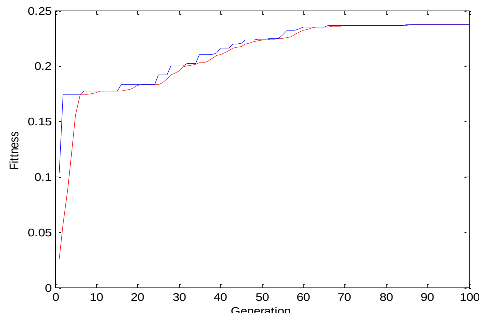

FIGURE 4 Population generation and fitness

The network has reached optimal after 100 generations. According to the trained network model, approximation error curve is shown in Figure 5.

From the figures, it's easy to see that error sum of squares decreases with the increasing numbers of iteration. At the eighth time, it starts to converge and finally tends to five. At the same time, the population's adaptability is on the increase. After the 70 generations, it tends to be a constant, which means that weight value of neural network iterates to optimal value. This paper adopts improved neural network, population size is 50. After 100 generations, optimal individuals have performed 4 times BP searches, and the error is under 0.1. That means the algorithm is succeeded in overcoming slow convergence rate.

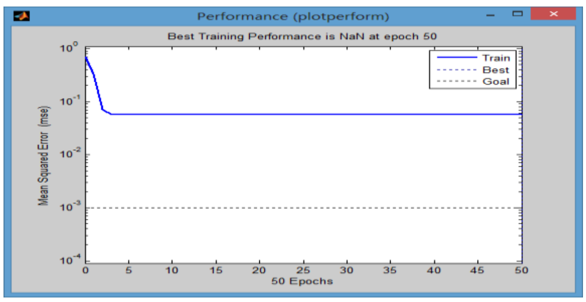

FIGURE 5 Error changing processes in network training

According to the training of network model, while the error reaches the least, the fitness degree is the highest and tends to be steady. Then the optimized weight value can be obtained. The final result is network algorithm model, which describes the equilibrium relationship between guaranteed shipping safety cost and cost of shipping safety failure. And it can be used for calculating the output – cost of shipping safety failure, under the input strategy of guaranteed shipping safety cost.

Conduct tests on sample data through built model, input each expense in the Matlab, then the normalization matrix is obtained. Compared with the actual expense, the specific data are shown in Table 4. It can be seen that numerical value in the final network algorithm matches actual value, and the error is in the allowed range.

TABLE 4 Calculated values and actual values of normalized cost of shipping safety failure

Actual values	Calculated values
-0.90	-0.90
-0.95	-0.90
-0.86	-0.90
-0.86	-0.92
-0.95	-0.92
1.00	0.62
-1.00	-1.00
-0.96	-0.92
-0.95	-0.45
0.25	0.62
0.06	-0.45
-0.90	-0.90
-0.95	-0.95
-0.97	-0.97

Select two shipping safety accidents from the samples.

Forecast and estimate the cost of shipping safety failure generated by trained genetic optimizing neural network, according to current guaranteed shipping safety cost input.

1) Estimate t the cost of shipping safety failure in Q strait shipping in April, 2010

The input layer of GA-BP is: "engineering cost of shipping safety management" is 162952 *yuan*, "shipping safety facilities fee" is 4555892 *yuan*, "environmental safety and health measures cost" is 2387 *yuan*, "cost of security inspection and overhaul" is 31699 *yuan*, "safety technology cost" is 93903 *yuan*, "education and publicity expense" is 148919 *yuan*, and "labor production fee" is 850139 *yuan*.

The cost of shipping safety failure calculated by genetic optimal neural network model is 220000 *yuan*, which is close to current actual loss 150000 *yuan*.

2) Estimate the cost of shipping safety failure in Q strait shipping in April, 2012

The input layer of GA-BP is: "engineering cost of shipping safety management" is 194613 *yuan*, "shipping safety facilities fee" is 12052466 *yuan*, "environmental safety and health measures cost" is 25522 *yuan*, "cost of security inspection and overhaul" is 143674 *yuan*, "safety technology cost" is 94666 *yuan*, "education and publicity expense" is 224121 *yuan*, and "labor production fee" is 1729584 *yuan*.

The cost of shipping safety failure calculated by genetic optimal neural network model is 99900 *yuan*, which is very close to current actual loss 100000 *yuan*.

5 Conclusions

The definition and component of shipping safety cost is discussed, aiming at the quantization of the equilibrium among the component factors. The equilibrium is between the structure of guarantee-purpose shipping safety cost and the cost of shipping safety failure. It is suggested that this equilibrium relationship essentially is the input and output of guaranteed shipping safety cost and cost of shipping safety failure. Considering the economic growth rate and discount rate based on the annual per capital GDP, the paper measures the value of casualties or missing caused by shipping accident or risk with the loss of social labor value. Then the death and missing in shipping accidents and risk could be quantified, which make it possible that both of the guarantee-purpose safety cost and the cost of safety failure could be valued by economic value. Genetic algorithm is adopted to optimize neural network, which improves the convergence rate and precision of neural network. Finally, GA-BP equilibrium model is established through network training. The economic value relation between guaranteed shipping safety cost and cost of shipping safety failure is determined with this model. The algorithm is tested through the empirical study. The results show that the error is small, and well within the acceptable limits. With the GA-BP model, cost of shipping safety failure could be estimated through input strategy of guaranteed shipping safety cost.

Acknowledgments

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