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Fast-prediction of automotive wiring-harness crosstalk based on GA-BP neural network model

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Abstract. This paper puts forward a kind of prediction model for auto-harness-wire crosstalk based on the GA-BP neural network model. Utilizing its peculiarity to the problem of nonlinear adaptive capacity, and giving full consideration to the influence of each factor on the auto-harness-wire crosstalk, the nonlinear mapping prediction model between 8 factors and auto-harness-wire crosstalk is set up. The experimental results show that, to achieve convergence, the BP network needs 403 times training while GA-BP just 30 times, and the correlation coefficient of GA-BP model prediction value and sample's actual test value reaches 0.999, showing strong correlation. The MAPE value of BP network prediction model and GA-BP network prediction model respectively are 4.7514 and 1.2370. And by comparing the output value of GA-BP network and the sample's actual values, it can be found that the auto-harness-wire crosstalk model built by the GA-BP neural network is superior to the traditional one in convergence speed and predicting precision. Finally, the effect weight of every factor to the crosstalk is determined by the weight analysis method, and the prediction model is simplified by reducing the input dimension of the model in maximum on the premise of guaranteeing the prediction precision.The research in this paper not only offers a reliable and effective method for the fast prediction of auto-harness-wire crosstalk, but also has enlightenment significance for the electromagnetic compatibility design of auto-harness-wire.

Key words. GA-BP neural network, auto-harness-wire, crosstalk prediction, analysis of the weight.

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1. Introduction

In recent years, there are many electrical devices and modules are linked by wires. Thus, it is not efficient to predict the crosstalk of wiring-harness by using the traditional methods such as finite element method, moment method and finite-difference time-domain method. In addition, the prediction models, which are established by most of the traditional methods, demand the simplification or approximate expression of the solving equations in ideal conditions. In this way, the predicted results have numerous drawbacks including low accuracy, poor portability and lack of universality. Therefore, it is essential to propose a more general method that is capable to predict automotive wiring-harness crosstalk quickly and efficiently.

Artificial neural network has the capability of implementing nonlinear mapping of different dimension spaces due to its special processing capacity for the nonlinear adaptability issues. It is widely applied in many aspects. Some domestic researchers adopted artificial neural network theories in the field of prediction of wiring-harness crosstalk and the results suggesting good performance. However, the models which were established by the researchers are mainly focused on condition that the ambient medium of conductors is uniform. Considerations of factors that are able to interfere wires such as insulating material and thickness are not involved in those models. Therefore, the researches mentioned above are not sufficient to provide practical instructions for analyzing and improving the crosstalk problems of wiring harness.

In this paper, genetic algorithm and neural network algorithm are combined to predict the crosstalk of automotive wiring-harness. By optimizing the traditional BP neural network of using the GA and Levenberg-Marquardt algorithm, drawbacks including the rate of convergence and the feature of falling into the local minimum point are improved. Experimental results demonstrated that the GA-BP neural network is superior to traditional BP neural network in numerous aspects such as the rate of convergence and prediction accuracy. Finally, weight analysis approach was performed to determine the interference coefficient of each factor in order to lower the predictive input dimension and simplify the predictive model effectively while ensuring accuracy. The proposed content in this paper provides an efficient fast prediction method for calculating the crosstalk of automotive wiring-harness.

2. Predictive module of wring-harness based on GA-BP

2.1. GA-BP neural network algorithm

Theoretically, BP neural network algorithm is capable to approach any functions by arbitrary precision. This overcomes the nonlinear problem that it is difficult to establish models by using specific data formulas. Despite the advantages, it also has numerous drawbacks including the low-speed convergence rate and nature of falling into the local minimum point which result in difficulty to obtain the globally optimal solution. GA can be adopted to optimize the BP neural network in three aspects which are network structure, learning rules and optimization of the connection weight. At present, the optimization of learning rules and network structure is not sufficient. Thus, this paper is mainly focus on the optimization of threshold value and weight value of BP neural network in order to establish the GA-BP neural network. GA-BP neural network searches the threshold value and weight value of the second-best solution by utilizing its global searching ability. The results are applied as the initial threshold value and weight value. Then, these values are trained by BP neural network. This method can be applied to avoid the situation that the neural network is caught in the local minimum point and to accelerate the convergence speed. Moreover, the dependence of the initial value for BP neural network can also be eliminated by implementing this method. The specific implementation process is shown in Fig. 1.

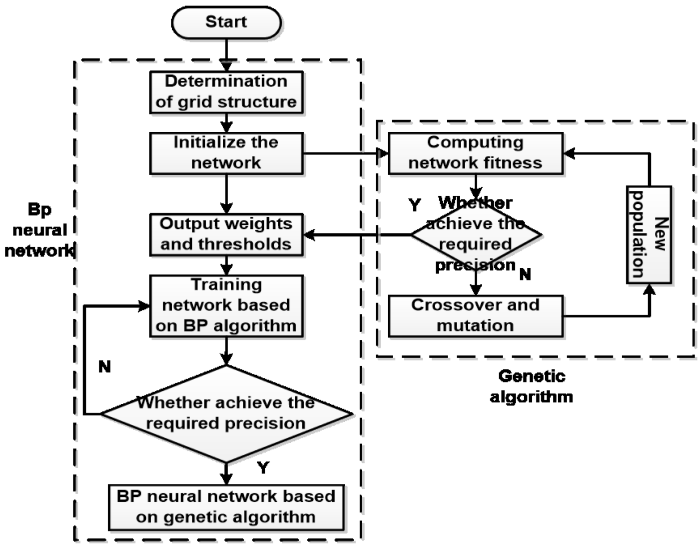

Fig. 1. The implementation flow chart of GA-BP neural network algorithm

2.2. Determination of the input-output characters of the GA-BP model

The lengths of the two parallel wires A and B are expressed as L_{A} and L_{B} respectively as shown in Fig. 2. The distance between A and B is represented as d. The distances between ground to the two wires, A and B, are expressed as h_1 and h_2 respectively. The radius of conductor, thickness of insulator and the dielectric coefficient of insulation medium are expressed as r_{A}, r_{B}, Δr_{A}, Δr_{B}, $\varepsilon_{\mathrm{rA}}$ and $\varepsilon_{\mathrm{rB}}$, respectively. Let wire A to be the interference wire and B to be the acceptor wire. The excitation voltage, impedance of source and load terminals are expressed as V_{S}, R_{S} and R_{L}, respectively. Assume that $R_{\mathrm{NE}} = R_{\mathrm{FE}} = R_{\mathrm{S}} = R_{\mathrm{L}} = 50$ where R_{NE} and R_{FE} are the near-end impedance and far-end impedance. According to the knowledge of electromagnetic field, crosstalk voltage V is related to L_{A}, L_{B}, d, h_1, h_2, r_{A}, r_{B}, Δr_{A}, Δr_{B}, $\varepsilon_{\mathrm{rA}}$, $\varepsilon_{\mathrm{rB}}$, V_{S} and f, which is frequency. In order to simplify the calculation, let $L = L_{\mathrm{A}} = L_{\mathrm{B}}$, $h = h_1 = h_2$, $r = r_{\mathrm{A}} = r_{\mathrm{B}}$, $\Delta r = \Delta r_{\mathrm{A}} = \Delta r_{\mathrm{B}}$,

$\varepsilon_r = \varepsilon_{\mathrm{rA}} = \varepsilon_{\mathrm{rB}}$. Thus, the number of coefficients related to the crosstalk voltage can be simplified from 13 to 8, which are L, h, r, $\varepsilon =_{\mathrm{r}}$, Δr, d, V_{S} and f. In this paper, these coefficients are all considered as an improvement compared to previous researches. The optimized predictive crosstalk model of wiring-harness has been established.

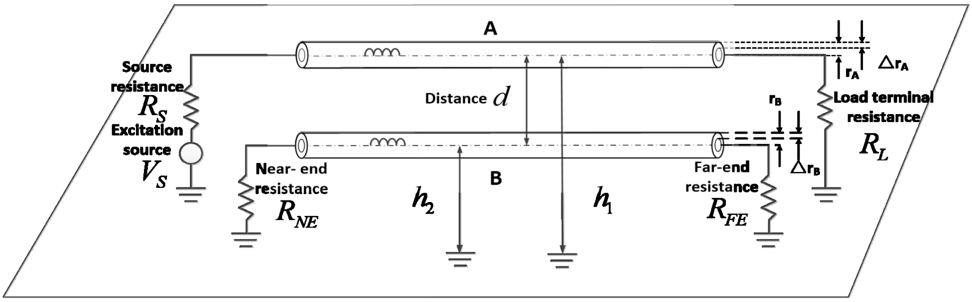

Fig. 2. The crosstalk model of two parallel wires in the auto-harness

3. Establish of GA-BP model of automotive wiring-harness crosstalk

From the demonstration that is mentioned above, the GA-BP neural network model of automotive wiring-harness can be established by mapping the related characters to the crosstalk value in order to optimize the predictive model. The crosstalk value V (V) is the network output of the predictive model and the related characters L (cm), h (cm), r (cm), ε_{r}, Δr (cm), d (cm), V_{S} (V) and f (MHz) are the network input.

There are 48 groups of experimental data that are shown in Table 1. These groups of data of near-end crosstalk values were obtained by using the combination of the moment method and multi-conductor transmission line method. The impact on the network output by the 8 network input characters are included. Therefore, the representativeness of these data is noteworthy. The first 32 groups of data are used as training samples and the last 16 groups are used as the testing samples.

It is theoretically proved that a specific network can approach any rational function and realize any nonlinear reflection with n-dimensional input to m-dimensional output if it has deviation, at least one S-type hidden layer and one linear output layer. In this paper, three layers of the neural network were applied to establish the predictive model of automotive wiring-harness crosstalk as shown in Fig. 3. There are 8 input vectors of layer X which are L, h, r, ε_{r}, Δr, d, V_{S} and f. The output layer of the network is the near-end crosstalk value V. The network training accuracy is related to the node numbers of the hidden layer in an undivided way. The principle of choosing node numbers is to add one to two nodes in order to accelerate the falling speed of error on the bases of that the problem can be solved doubtlessly. It should be noticed that there is no certain theoretical functions for determining the quantity of node number. Numerous empirical equations are generally applied to determine the node numbers which is shown by equations (1)–(3). In this paper, these equations are adopted with attempts to determine the node number of hidden layer.

$$l = \sqrt{n+m} + \alpha\,, \tag{1}$$

$$l = \log_2 n\,, \tag{2}$$

$$\sum_{i=1}^{n} C_i' > k\,. \tag{3}$$

Table 1. The original data table of auto-harness-wire crosstalk

Sample number	L (cm)	h (cm)	r (cm)	ε_{r}	δr (cm)	d (cm)	V_{S} (V)
1	50	3.0	0.05	2.3	0.05	2.0	1.0
2	50	3.0	0.05	2.7	0.05	2.0	1.0
3	50	3.0	0.05	3.0	0.05	2.0	1.0
4	15	3.0	0.05	3.5	0.05	2.0	1.0
5	45	3.0	0.05	3.0	0.05	2.0	1.0
6	75	3.0	0.05	3.0	0.05	2.0	1.0
7	90	3.0	0.05	3.0	0.05	2.0	1.0
8	50	3.0	0.05	3.0	0.05	2.0	1.0
9	50	3.0	0.05	3.0	0.02	2.0	1.0
10	50	3.0	0.05	3.0	0.10	2.0	1.0
11	50	3.0	0.05	3.0	0.25	2.0	1.0
12	50	3.0	0.05	3.0	0.40	2.0	1.0
13	50	3.0	0.01	3.0	0.05	2.0	1.0
14	50	3.0	0.10	3.0	0.05	2.0	1.0
15	50	3.0	0.25	3.0	0.05	2.0	1.0
16	50	3.0	0.25	3.0	0.05	2.0	1.0
17	50	3.0	0.05	3.0	0.05	1.5	1.0
18	50	3.0	0.05	3.0	0.05	3.0	1.0
19	50	3.0	0.05	3.0	0.05	4.0	1.0
20	50	3.0	0.05	3.0	0.05	4.5	1.0
21	50	0.5	0.05	3.0	0.05	2.0	1.0
22	50	2.0	0.05	3.0	0.05	2.0	1.0
23	50	4.5	0.05	3.0	0.05	2.0	1.0
24	50	6.0	0.05	3.0	0.05	2.0	1.0
25	50	3.0	0.05	3.0	0.05	2.0	0.8
26	50	3.0	0.05	3.0	0.05	2.0	1.5
27	50	3.0	0.05	3.0	0.05	2.0	2.0
28	50	3.0	0.05	3.0	0.05	2.0	2.5
29	90	3.0	0.05	3.0	0.05	2.0	1.0
30	90	3.0	0.05	3.0	0.05	2.0	1.0

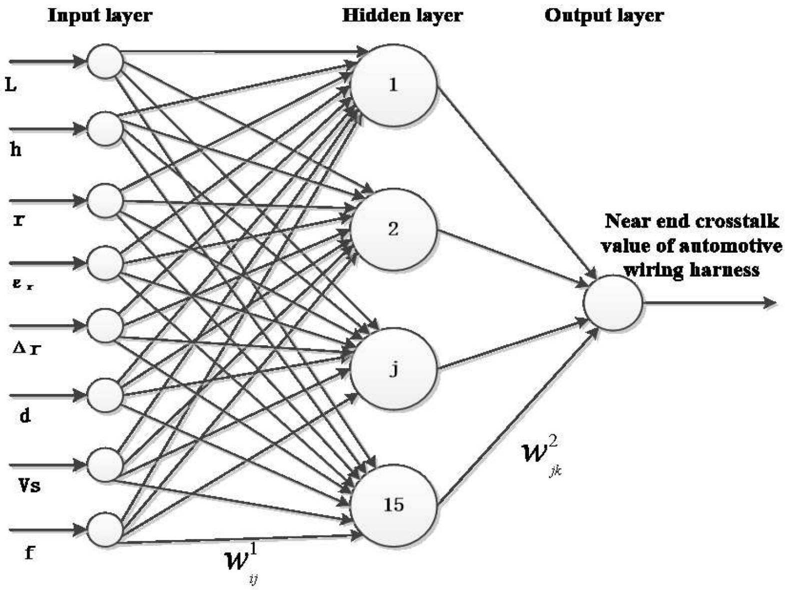

Fig. 3. The crosstalk model of two parallel wires in the auto-harness

3.1. Optimization of weight and threshold value using GA algorithm

The BP neural network requires the optimization with GA before its training. The genetic algebra, crossover probability and mutation probability are set as 150, 0.95 and 0.09 respectively. The specific steps are:

(1) Set initial weight and threshold value as chromosome and compile codes.

(2) Generate initial population and the scope should not be too big. It is set as 50 and the genetic algebra is set as 100.

(3) Obtain the fitness function of the GA optimizing network which is determined by the learning error generated from population training of samples.

(4) Use the MATLAB tool box GOAT to solve the model.

The accuracy of the calculation results is influenced by the data range of initial data. Therefore, the operation of initial data is necessary before obtaining the results. The method is to normalize the initial data at first and then perform inverse transformation of the network output to obtain the actual output. The transformation formula and inverse variation formula are shown as equation (4) and (5) below:

$$y = \frac{x - x_{\min}}{x_{\max} - x_{\min}}, \tag{4}$$

$$x = x_{\min} + y\left(x_{\max} - x_{\min}\right), \tag{5}$$

where x and y are the values before and after the transformation, $x_{\min}$ and $x_{\max}$ are the maximum value and the minimum value of the samples.

The changing curve of the fitness value during the GA algorithm process is shown in Fig. 4. It can be seen in the figure that the increasing speed of the fitness value at the initial stage of the genetic iterations is very fast. This trend is relatively mitigated at the thirteenth generation. The individual fitness value and average optimized fitness value reach the peak at the 50th generation.

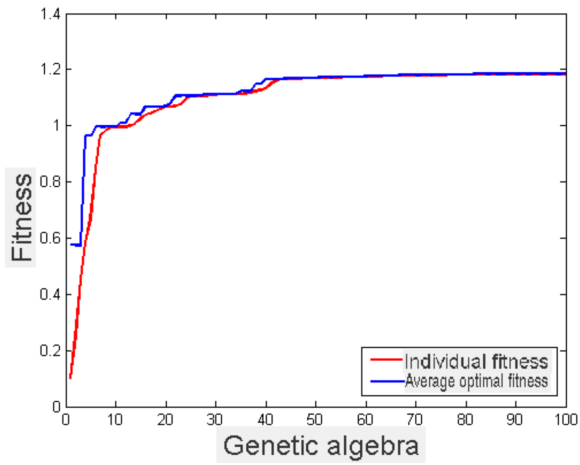

Fig. 4. The fitness curves of ga algorithm

The related training characters of the BP neural network should be determined when the weight & threshold value are optimized with GA algorithm. Then, the neural network training is performed. Since the determination of related training characters of the BP network are significant to the performance and results of neural network, the Levenberg-Marquardt algorithm is adopted in this paper to perform the network training. The learning speed rate, factor of momentum and expected error are 0.2, 0.5 and 10^{-7}, respectively. As the characters are determined, the GA-BP predictive model was established and trained.

3.2. Comparison between training results of GA-BP and BP model

The training error curves of GA-BP and BP predictive model are shown in Fig. 5 and Fig. 6. As shown in the figures, it requires 30 and 403 times of training for GA-BP and BP respectively. In addition, the rate of convergence of GA-BP is also faster than BP model. This proves that the GA-BP model can be adopted for the automotive wiring-harness crosstalk predictive model with faster convergence rate. It can be seen in Fig. 7 that the related coefficient between the crosstalk value of the GA-BP model and actual testing samples reaches 0.999 which proves strong correlation. In this way, the proposed predictive model of automotive wiring-harness crosstalk based on the GA-BP algorithm is capable for reflecting the nonlinear relationship between the crosstalk value and the related characters.

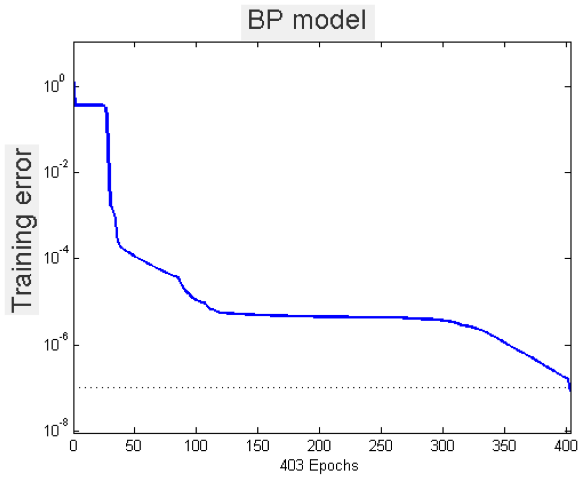

Fig. 5. The training error curve of ga-bp model

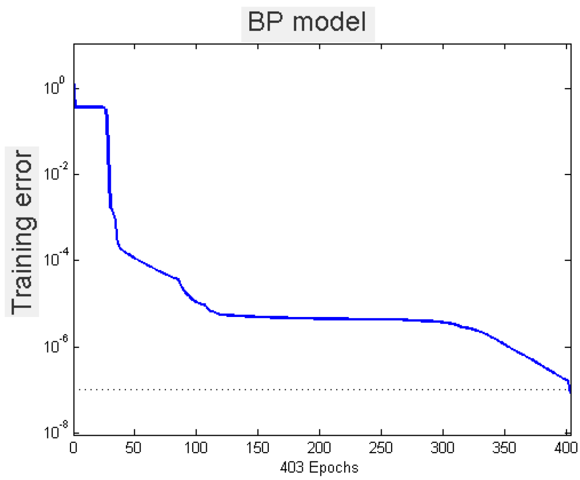

Fig. 6. The training error curve of bp model

After many times of training, the GA-BP and BP networks will convergence to achieve the training purpose. Then, anti-normalization are performed and results are compared in Table 2.

Calculating formula based on mean absolute percentage error (MAPE) is show in equation(6)

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i' - y_i}{y_i} \times 100\right| \tag{6}$$

In equation (6), y_i' expresses the predictive value of the network output and y_i is the actual value of the testing samples.

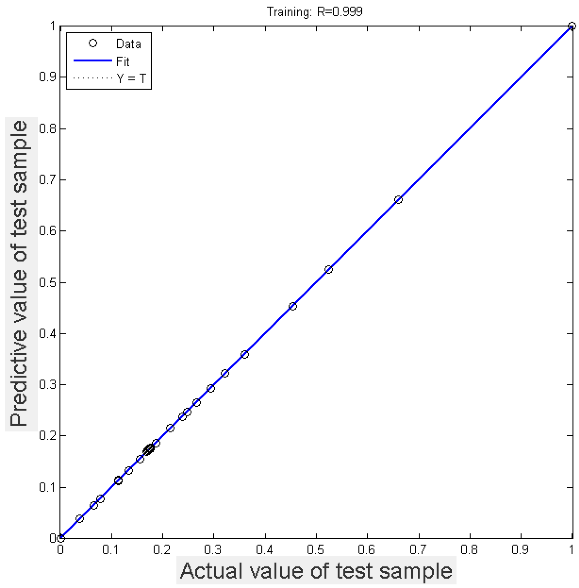

Fig. 7. The scatter plot of the actual value test samples and ga-bp model prediction

Table 2. The comparison of the actual value and the predicted value of the neural network

Testing samples	Actual value	BP PV*	Error (%)	GA-BP PV*	Error (%)
1	0.0191	0.0190	0.5236	0.0191	0
2	0.0.90	0.0193	0.1579	0.0190	0
3	0.0114	0.0121	6.4393	0.0123	7.8947
4	0.0228	0.0225	1.5219	0.0227	0.4386
5	0.0190	0.0191	0.5263	0.0191	0.5263
6	0.0191	0.0202	5.7592	0.0190	0.5236
7	0.0193	0.0194	0.5181	0.0194	0.5181
8	0.0195	0.0192	1.5385	0.0194	0.5128
9	0.0158	0.0158	0	0.0157	0.6329
10	0.0113	0.0113	0	0.0113	0
11	0.0096	0.0064	33.3333	0.0097	1.0417
12	0.0215	0.0201	6.5116	0.0215	0
13	0.0228	0.0224	1.7544	0.0222	2.7027
14	0.0343	0.0321	6.4140	0.0329	4.0816
15	0.0411	0.0414	0.7299	0.0412	0.2433
16	0.0823	0.0749	8.9915	0.0809	1.7011

PV* - predictive value

This character is applied to evaluate the actual performance of the GA-BP neural network predictive model. Generally, the predictive accuracy increases with the decreasing of the MAPE value. Specially, the predictive accuracy is considered as relative high if MAPE is less than 10. The MAPE value of the BP network predictive model and the GA-BP model are 4.7514 and 1.2370, respectively, by calculation.

The MAPE value can be obtained by the comparison between the output value of the neural network and the actual value of samples. Compared to the traditional BP neural network model, the automotive wiring-harness model which is established by GA-BP has better accuracy and faster rate of convergence. Thus, the wiring-harness crosstalk can be predicted in a quick way. Meanwhile, the GA-BP model considers the relative physical dimension, wire position and the 8 characters such as the relative dielectric constant of the insulating layer. This provides essential supplement of the automotive wiring crosstalk predictive model.

4. Analysis of impact factor and model simplification

4.1. Weight analysis method

In the neural network models, the input lay and the hidden layer are connected by weight value. Similarly, the hidden layer and the output layer are also connected by weight value. The weight value between the input layer and the output layer reflects the impact extent from input to output. Garson proposed a method to acquire the weight value from input to output by using neural network which is shown in equation (7).

$$I_j = \frac{\sum_{m=1}^{Nh}\left(\left(\left|w_{jm}^1\right| \Big/ \sum_{k=1}^{Ni}\left|w_{km}^1\right|\right)\times\left|w_{mn}^2\right|\right)}{\sum_{k=1}^{Ni}\left(\left(\sum_{m=1}^{Nh}\left|w_{km}^1\right| \Big/ \sum_{k=1}^{Ni}\left|w_{km}^1\right|\right)\times\left|w_{mn}^2\right|\right)} \tag{7}$$

In equation (7), I_j is the weight impact value of nth output character that is influenced by the jth input character. Symbols N_i and N_h denote the node numbers of input layer and hidden layer, respectively. Quantities w^1 and w^2 are the connection weight value between the input layer and the hidden layer, and analogous value between the hidden layer and the output layer. Indices J, m and n are signs of the nodes. With the increase of I_j, which is the weight value from input to output, the impact weight radio increases correspondingly. It also can be considered that the character has considerable impact on the output if the weight value is relatively higher than the others.

As mentioned previously, there are 8 characters as the impact factors of the GA-BP neural network predictive model. The weight analysis method is applied to determine the influence to the crosstalk by these factors. It is based on the weight values that connect the input layer, hidden layer and the output layer after the GA-BP network training.

4.2. Simplification of the predictive model of automotive wiring-harness crosstalk based GA-BP neural network

The input characters have different impact extent on the crosstalk value. The order from bigger impact to smaller impact is the wire length L, frequency f, distance between wire and ground h, excitation voltage V_{S}, relative dielectric constant of insulation layer ε_r, relative distance between wires d, radius of wire r and thickness of insulation layer Δr. The weight coefficient of r and Δr is quite small, 3.2 % and 1.1 %, respectively. The influence can be ignored. However, characters including L, f and d have significant impact on the crosstalk value. These characters play important role in the GA-BP predictive model. According to the weight coefficient of each character in Fig. 8, the model can be simplified by considering the different impacts of characters.

(1) According to the weight of these characters, r and Δr can be ignored and the rest six characters are considered as input. Quantity V is the output of the predictive model based on GA-BP. Through the designed tests, the network structure of the model is determined as 6-12-1. For the initial experimental samples, the simplified conditions includes $r = 0.05\,\mathrm{cm}$ and $\varepsilon_{\mathrm{r}} = 3$, 24 groups of training samples and 12 group of testing samples. After calculation, MAPE can be obtained as 1.5206 with the consumption of time of 4.465 s.

(2) Establish the predictive model based on GA-BP that involves the input of L, f, h, V_{S} and ε_{r}. The output of the model is V. The network structure is determined as 5-10-1 by performing tests. For initial experimental samples, the simplified condition includes $r = 0.05\,\mathrm{cm}$, $\Delta r = 0.05\,\mathrm{cm}$ and $d = 2\,\mathrm{cm}$, 20 groups of training samples and 10 groups of testing samples. After calculation, MAPE can be obtained as 1.7092 with the consumption of time of 4.749 s.

(3) Choose L, f, h and V_{S} as input and V as output, the GA-BP based predictive model can be established. The network structure can be determined as 4-7-1. For initial experimental samples, the simplified conditions include $r = 0.05\,\mathrm{cm}$, $\Delta r = 0.05\,\mathrm{cm}$, $d = 2\,\mathrm{cm}$ and $\varepsilon_{\mathrm{r}} = 3$, 16 groups of training samples and 8 groups of testing samples. After calculation, MAPE can be obtained as 1.3860 with the consumption of time of 2.836 s.

(4) Let L, f and h be input values and V the output. Then, the GA-BP based predictive model can be established. The network structure can be determined as 3-5-1. For initial experimental samples, the simplified conditions include $r = 0.05\,\mathrm{cm}$, $\Delta r = 0.05\,\mathrm{cm}$, $d = 2\,\mathrm{cm}$, $\varepsilon_{\mathrm{r}} = 3$, $V_{\mathrm{S}} = 1\,\mathrm{V}$, 12 groups of training samples and 6 groups of testing samples. After calculation, MAPE can be obtained as 1.0370 with the consumption of time of 2.882 s.

5. Conclusion

In order to overcome the drawbacks including complexity and lack of time efficiency of calculating the actual automotive wiring-harness by using the traditional methods, a predictive model based on neural network is proposed in this paper. The GA algorithm and Levenberg-Marquardt algorithm are adopted to optimize the traditional BP neural network. The experimental results show that it only requires 30 times of training by using GA-BP method which is superior to BP method which requires 403 times of training. In addition, the predictive model has relative coefficient of 0.999 which proves strong relativity. After calculation, MAPE of BP and GA-BP can be obtained as 4.7514 and 1.2370, respectively. By comparing the output value of neural network model and actual value of samples, it can be seen that GA-BP model owns better performance including rate of convergence and predictive accuracy compare to the BP model. Finally, the input characters are analyzed by using the weight analytical method in order to determine the individual impact factor. Under the condition of ensuing the accuracy and efficiency, dimensionality reduction is performed according to their own impact extent. The simplified condition includes $r = 0.05\,\mathrm{cm}$, $\Delta r = 0.05\,\mathrm{cm}$, $d = 2\,\mathrm{cm}$, $\varepsilon_\mathrm{r} = 3$, $V_\mathrm{S} = 1\,\mathrm{V}$, L, f, h are the input values and V is the output value. Under above condition, the GA-BP based predictive model can effectively be simplified. The demonstrated research has practical guiding significance to the analysis of automotive wiring-harness crosstalk and related EMS design.

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