AGING PREDICTION OF RUBBER ELEMENT BY NEURAL NETWORK

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Abstract

The model for predicting the rubber aging capability by method of neural net- work was presented in this paper. Using this model, the aging capability of "O" type rubber sealing ring under the condition of different time was calculated and compared with experimental. The result showed that the model is of high precision It can be used in engineering for solid rocket motor developing.

1 Introduction

Rubber was used widely in the fields of astronautics. The capability of rubber will be weakened step by step in the course of preservation and using, down to useless because aging is the natural of rubber. For the sealed rubber applied to solid rocket motor, it`s failure would lead to losing and worthlessness of the whole produce function. So the rubber aging is very important to missile and rocket. Predicting the rubber aging capability precisely is urgent.

Many researches about rubber aging have been done since 1960s[1,2,3]By the work of speed-up aging experiment and monitoring the natural preservation long time ,there is a quiet great progress to the changing rule of the aging capability under the condition of different temperature、stress and humidity. According to the experimental data ,Arrhenius built the relation between the capability changing and aging time、aging temperature, which had an effect on big evaluating the rubber aging[4,5].

The speed-up aging experiment has acted on recognizing the nature of aging. But there are two defects：that is requiring a great deal of experiment, the data-processing using regressive statistics and the data must be regularity. So it is necessary to search a new method for aging predicting

Artificial neural network is a kind of not-liner adaptive system. It is made of a lot of simple basic neural unit connecting one another. It is an important branch of artificial intelligence. The neural network can realize reflection approaching from input to output at random. Compared with tradition data processing method, it is of advantage in dealing with complex multi-dimensions not-liner problem.. This method has been used in macromolecule material designing and capability prediction widely. The reference [6] had a summarizing to applying neural network to researching material ingredient and technical process.

In this paper ,the model about rubber aging was built. Rubber aging capability according to time sequence was predicted and compared with the experimental The result showed the consistent character and the model can be used in rubber aging prediction.

2 To Built the Model for Rubber Aging Predicting

2.1 To Built Bp Neural Network

At the present time, the most representative and the most useful model is BP network among all the kinks of neural network model. The BP model is made of one input layer、one or more hidden layer and one output layer. Input the information, the hidden node were dealt with the function and then be sent to the output layer.

Compare the output result with the expectation. Transmit the error back and revise the weighted coefficient till the error satisfy the request.

A typical 3 layer BP Neural network as shown in Figure 1

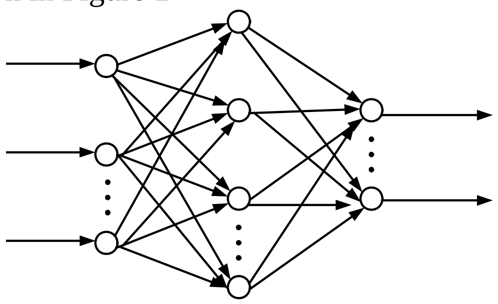

Figure1. 3 layers BP network construction

The sigmoid function always as the node effective function

$$f(x)=\frac{1}{1+e^{-x}} \qquad (1)$$

The cells number in input layer、hidden layer and output layer were N、L、M，The input vector $X=\{x_1,x_2,\cdots\cdots x_N\}$ ，The output vector in hidden layer $H=\{h_1, h_2, \cdots\cdots h_L\}$ ，The output vector in output layer $Y=\{y_1, y_2, \cdots\cdots y_M\}$,The expected output vector $D=\{d_1, d_2, \cdots\cdots d_M\}$ ，The weighted coefficient from input cell i to hidden cell j was V_{ij}，The weighted coefficient from hidden cell j to output cell k was W_{jk}，So the cells in the hidden layer were showed:

$$h_j=f\left(\sum_{i=1}^{N}(v_{ij}x_i)\right) \qquad (2)$$

The cells in output layer were showed：

$$y_k=f\left(\sum_{j=1}^{L}w_{jk}h_j\right) \qquad (3)$$

S samples had been trained. The general average error

$$E=\frac{1}{2S}\sum_{1}^{s}\sum_{k==1}^{m}(y_k-d_k)^2 \qquad (4)$$

was the training aim function. According the Grads Decline Rule. The error items in hidden layer and output layer should be

$$\delta_k=(d_k-y_k)y_k(1-y_k) \qquad (5)$$

$$\delta_j^*=h_j(1-h_j)\sum_{k=1}^{m}(\delta_k w_{jk}) \qquad (6)$$

the rectify quantity about the weighted coefficient to every cell should be

$$\Delta w_{jk}(n)=\eta\delta_k h_j, \qquad (7)$$

$$\Delta v_{ij}(n)=\eta\delta_j^* x_i$$

Here, η is a normal interval controlling the training speed, and $0<\eta<1$. During the training, repeat calculating the input and output errors till the average error of the network meets the requirement.

2.2 Model of the mechanical behaviors concerning rubber aging

Considering that a three-layer BP network is efficient enough to approach any continuous functions, as well as the practical request, the three-layer BP network model with four input units, four hidden units, two output units, and S training samples was selected in this paper.

Suppose the time sequence relating rubber aging capability be $x_1, x_2, x_3, \cdots\cdots x_N$. Let $\{x_1,x_2,x_3,x_4\}$, $\{x_2,x_3,x_4,x_5\}$, $\{x_3,x_4,x_5,x_6\}$,…, $\{x_{N-3},x_{N-2},x_{N-1},x_N\}$ be input vectors after being divided into S samples, the corresponding output vectors are respectively $\{\frac{1}{1+e^{-x_4}},\frac{1}{1+e^{-x_5}}\}$, $\{\frac{1}{1+e^{-x_5}},\frac{1}{1+e^{-x_6}}\}$, $\{\frac{1}{1+e^{-x_6}},\frac{1}{1+e^{-x_7}}\}$,…, $\{\frac{1}{1+e^{-x_{N-1}}},\frac{1}{1+e^{-x_N}}\}$ 。

The behavior parameters are suggested to be tensile strength, break elongation ration, or permanent compression deformation. For the selected S samples, the total average error E is taken as control objective.

3 Calculation of the rubber aging capability

The rubber mechanical behaviors change gradually in the aging process. The reference[1] investigated the heat aging of the "O" type rubber sealing ring at the temperature 105℃, 125℃, 150℃, and 175℃under both application and standard testing states. Analysis showed that, at the certain temperature, the relationship between the permanent compression deformation k and the time agreed with the function:

$$\ln(1-k) = A + Bt^{0.3} \qquad (8)$$

A and B were respectively –0.01985 and –0.06346 in the aging under 150℃, with the related coefficient higher than 0.999. In the present paper, the permanent compression deformation under aging temperature 150℃ at different aging times were initially calculated according to the function, then the data in the range of 22h to 562h were trained in 24 groups. The trained calculation results and the corresponding training errors were listed in table 1.

Table1.

Aging Times (h)	Permanent Compression Deformation[1]	Trained Calculation Results	Corresponding Training Errors (%)
22	0. 1653		
42	0. 1936		
62	0. 2129		
82	0. 2278	0. 2281	0. 13
102	0. 2402	0. 2407	0. 08
122	0. 2508	0. 2504	-0. 16
142	0. 2601	0. 2596	-0. 19
162	0. 2685	0. 2681	-0. 15
182	0. 2760	0. 2758	-0. 07
202	0. 2830	0. 2828	-0. 07
222	0. 2894	0. 2894	0
242	0. 2953	0. 2954	-0. 03
262	0. 3009	0. 3011	0. 06
282	0. 3062	0. 3064	0. 06
302	0. 3112	0. 3114	0. 06
322	0. 3159	0. 3161	0. 06
342	0. 3203	0. 3206	0. 09
362	0. 3246	0. 3249	0. 09
382	0. 3287	0. 3289	0. 06
402	0. 3326	0. 3328	0. 06
422	0. 3364	0. 3365	0. 03
442	0. 3400	0. 3400	0
462	0. 3434	0. 3435	0. 03
482	0. 3468	0. 3467	-0. 03
502	0. 3501	0. 3499	-0. 06
522	0. 3532	0. 3530	-0. 06
542	0. 3562	0. 3559	-0. 08
562	0. 3592	0. 3588	-0. 11
582	0. 3621	0. 3615	0. 13
602	0. 3648	0. 3642	0. 16
622	0. 3676	0. 3668	0. 19
642	0. 3702	0. 3694	0. 21
662	0. 3728	0. 3718	0. 27
682	0. 3753	0. 3742	0. 29
702	0. 3777	0. 3765	0. 29
722	0. 3801	0. 3788	0. 34
742	0. 3824	0. 3810	0. 34
762	0. 3847	0. 3832	0. 42

The maximum relative error is 0.11% in table 1. Additionally, the convergence process of the average error in training was illustrated in figure.2.

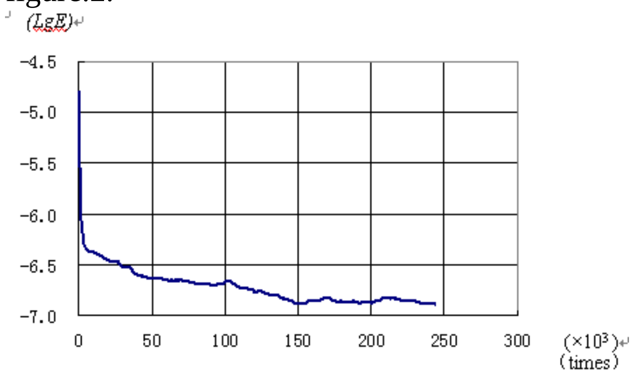

Figure. 2 The convergence process of the average error in training

On the completion of training, the calculating model was built concerning the permanent compression deformation of the "O" type rubber ring in the 150℃ heat aging. The calculation results in the range of 582h to 762h were listed in table 2. Clearly, the maximum relative error is 0.42%, indicating the efficiency of the model for predicting the rubber aging capability.

4 Conclusion

The properties were calculated in the rubber aging by BP neural network model. Under a certain temperature, the aging data (not less than 4) with the same time interval were sufficient enough to establish a BP model for predicting the rubber mechanical properties (tensile strength, elongation ration, or permanent compression deformation). The results show that the model is capable of predicting the rubber aging capability in high precision and therefore applicable in practical engineering.

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