Analysis on Mean Time between Failures Based on Artificial Neural Network

Heqing Li[1,2]
1 Center South University, Changsha, 410083, China
2 Changsha University of Science and Technology, 410076, Changsha, China
Email: liheqing@sina.com

Qing Tan
Center South University, Changsha, 410083, China
Email: jds-share@163.com

***Abstract*—Aimed at the reparable characteristic of the mechanical product, a method of the reliability model recognition of mean time between failures based on the BP neural network was developed, and a method of parameter estimation of reliability model based on adaptive linear network was proposed by means of theory of artificial neural network with MATLAB and reliability engineering theory. By network test and numerical simulation, reliability model recognition system and reliability parameters estimation system are verified. The results obtained from the simulation is better than those from the reliability paper for the common reliability model in engineering reliability and indicate the method is feasible. According to the method, the distribution model and function of reliability for mean time between failures of mechanical product were gained by this means.**

***Index Terms*—mean time between failures, model recognition, parameter estimation, artificial neural network**

I. INTRODUCTION

In the study of mechanical product reliability, we mainly hope that life distribution law and reliability parameters of random, such as life, material strength and load of mechanical product, are expected to be obtained. Life distribution is one of the main mathematical methods in describing product reliability. If mastering product life distribution, we should be beneficial to improve product reliability and work out scientifically product maintenance strategy. Mean time between failures (MTBF) of product describes mean value of working time between failures. It is able to evaluate manufacture, application and maintenance quality of the product. Thus it is a very important performance index in analyzing the product reliability [1-2].

At present, mechanical product reliability has been widely studied, and we adopt traditionally the methods of graph or mathematical statistical [3-5]. The first method is direct and rough, but the second one should estimate parameter first and its results depend on the level of accuracy. Recently, neural network has been widely applied in the study of mechanical product reliability. Some scholars have applied neural network to research on life distribution model and parameter estimation of product. Gao Shang has established recognition model of life distribution type through using life data and neural network of training tutor values [6]. Yan Yushan has analyzed on main fan first failure time based on BP neural network technique [7]. Wu Yueming has obtained from the simulation results that indicate BP network needs smaller space occupation and its generalization ability is better than RBF network when solving life distribution model [8]. Ao Changlin has gained the model parameters and function of reliability for the first failure time of a tractor based on neural network [9]. He Yuyang has got the curve of reliability of brake system in vehicles based on BP neural network [10]. Mao Zhaoyong has presented that the improvement genetic algorithms can solve maximum likelihood estimation parameter estimation through neural network, and the result shows that the optimization method of maximum likelihood estimation parameter estimation is feasible [11]. Above methods only individually analyzed reliability model recognition or reliability parameters estimation through neural network theory.

The neural network solving complex relationship among the factors of reliability assessment in nonlinear, discrete system, such as the mechanical product, has unique advantage. Meantime, this method has better mode organization form and computer working platform, therefore, it has broad application prospects. This paper established mechanical product life distribution model and parameters estimation model through neural network. Through above models, the distribution model and parameters estimation model for mean time between failures of the vibratory roller were gained.

II. RECOGNITION SYSTEM OF RELIABILITY MODEL BASED ON BP NEURAL NETWORK

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TABLE I. PARTS OF LEARNING SAMPLE IN RECOGNITION RELIABILITY DISTRIBUTION

distribution	percentile									
	0.05	0.15	0.25	0.35	0.45	0.55	0.65	0.75	0.85	0.95
E(0.2)	0.0121	0.0394	0.0697	0.1048	0.1452	0.1915	0.2554	0.3378	0.4622	0.7298
E(0.5)	0.0122	0.0392	0.0698	0.1054	0.1458	0.1948	0.2561	0.3394	0.4644	0.7340
N(1.0,0.2)	0.2130	0.2528	0.2731	0.2887	0.3044	0.3166	0.3320	0.3508	0.3743	0.4080
N(1.0,1.2)	-0.2326	-0.0512	0.0401	0.1155	0.1777	0.2346	0.2973	0.3644	0.4661	0.6351
L(1.0,0.3)	0.1733	0.2099	0.2315	0.2562	0.2797	0.3047	0.3287	0.3607	0.4051	0.4831
L(1.0,1.1)	0.0203	0.0365	0.0547	0.0782	0.1024	0.1414	0.1885	0.2622	0.4395	0.7199
W(1.2,1.0)	0.0197	0.0603	0.0932	0.1321	0.1682	0.2160	0.2693	0.3377	0.4359	0.7199
W(2.2,1.0)	0.0868	0.1478	0.1876	0.2251	0.2623	0.2944	0.3303	0.3765	0.4318	0.5403

Reliability model plays a virtual role in analyzing product reliability. According to collection of experimentation or field data, some useful information is obtained by analyzing fault data, thus reliability model can be recognized properly. Recognition system of reliability model usually includes fault data pretreatment, feature extraction and classifier.

Because BP neural network has powerful function of pattern matching and nonlinear mapping, it can construct recognition system of complex reliability model.

A. A model structure of BP neural network

A typical structure of a three layer forward neural network is shown in fig.1. It includes input layer, hidden layer and output layer. In fig.1, circles represent neurons. Connecting line having weight w_{ij} between circles represents interaction strength between neurons, where w_{ij} is the connection weight between neuron i in the k-th layer and neuron j in the (k-1)-th, b_{ki} (i=0~n) is the threshold of neurons, x_i (i=0~n) is the input of neurons, y_j (j=0~m) is the output of neurons and F(·) is a transfer function from the (k-1)-th layer to the k-th layer.

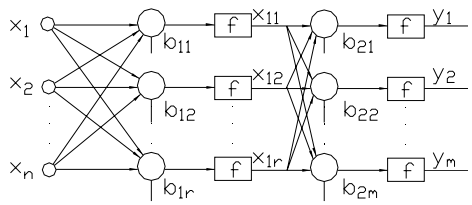


Figure 1. Model structure of BP neural network

Structure design of network is related to layers of network, neurons in each layer, initial values and learning rate, etc. After determining structure of BP network, using input and output sample sets train designed network, namely, the weights and thresholds of network is learned and adjusted continually, so that the designed network implements relationship between input and output.

to estimate the error of the preceding layer again and again. The estimates of error of the other layers again and again. The estimation of error of the other layers can be obtained. In this way, it may form the process that transmits the error of the output layer to the input layer of network along the transmission right about of the input signals. Thereby, the algorithm is called the Back Propagation algorithm. And the non-cycle network that uses the BP algorithm to learn is called BP network. Its course of learning is just the course of training. The training is to adjust the weights among neurons by certain manner when the samples vectors are put into neural network. The specific realizations of BP learning algorithm follow as:

1) Initialize right aggregate w_{ij}, get the value of the lesser stochastic nonzero;

2) Give many pairs of input and output samples (X_p, D_p), where p=1, 2, …, p, i is number of training mode pairs; X_p is input vectors, D_p is output expectation vectors.

3)Calculate their actual output Y_p=(y_{1p}, y_{2p}, …, y_{mp}), in this course, many times of positive spread calculation is done in terms of the different number of network layer.

4) Evaluate the objective function of the network, and the output error value can generally be denoted as:

$$E = \frac{1}{2}\sum_{p=1}^{p}\sum_{j=1}^{m}(d_{jp} - y_{jp})^2 \cdot \quad (1)$$

5) Judge whether the network satisfies the precision

$$E \le \varepsilon . \quad (2)$$

Where ε is the desired precise, the process of training will continue until the precision is attained.

6) Adjusting the weights through dropping off one by one along the reverse according to grads can be computed by:

$$W_{ij}(t+1) = W_{ij}(t) - \eta \frac{\partial E}{\partial W_{ij}} . \quad (3)$$

C.Recognition system design of reliability model based on BP neural network.

In designed need recognition types, distribution models are likely to be categorized into four types: exponential, normal, lognormal, and WEIBULL distribution. Method of random simulation by MATLAB produces four sorts of different parameters distributions, which have ten groups of random sequences as the initial sample data individually. Then selection of percentile of statistical features in a probability distribution is regarded as training sample set of recognition system. In order to reduce sample feature absolute value has influence on approximation accuracy, 10 percentiles in each sample is likely to need normalization processing. Parts of learning sample are shown in table 1, E is exponential distribution, N is normal distribution, L is lognormal distribution, and W is two parameters. Density function of WEIBULL distribution is given by:

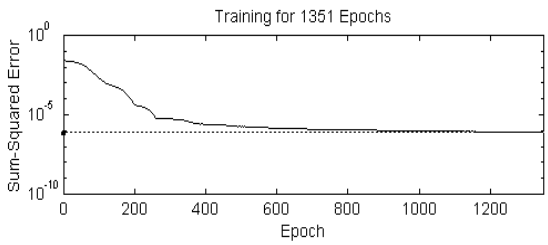
$$f(t)=\frac{\beta}{\eta}(\frac{t}{\eta})^{\beta-1}e^{-(\frac{t}{\eta})^{\beta}}\ (t\geq 0). \qquad (4)$$

Where, β is shape parameter, and η is scale parameter.

According to recognition types and learning sample, objective response of network is given as follow:

$$y=\begin{bmatrix}1\cdots10\cdots00\cdots00\cdots0\\0\cdots01\cdots10\cdots00\cdots0\\0\cdots00\cdots01\cdots10\cdots0\\\underbrace{0\cdots0}_{10}\underbrace{0\cdots0}_{10}\underbrace{0\cdots0}_{10}\underbrace{1\cdots1}_{10}\end{bmatrix}. \qquad (5)$$

After determining the input sample and the output response, unit numbers of the input layer and the output layer are also determined. Experiment indicates that the numbers of layers of BP neural network of recognition reliability model is three. The numbers of neurons of the input layer, hidden layer and output layer are 10, 4, 4 respectively. The transfer function of hidden layer and output layer is a sigmoid function, namely, it is $f(s)=\frac{1}{1+e^{-s}}$. Selection of related parameters: the most learning times is m_e=10000, the least expectation error is e_g=0.0001, and the learning rate of adaptation of weight is



η=0.01. In process of training network, the change curve of error is shown in fig.2. The sum of squares of error is close to 10^{-4} through 1351 times training network.

Figure 2. The change curve of the sum of squares of error

Finally, method of random simulation produces respectively 20 groups of exponential, normal, lognormal and WEIBULL distribution as testing sample, trained neural network recognizes these data, its recognition rate is shown in table 2.

III. RELIABILITY PARAMETERS ESTIMATION BASED ON ADAPTIVE LINEAR NEURAL NETWORK

After recognizing reliability model of system, we can design reliability model. Through analyzing related life data of system, distribution law and parameter of random variables can be determined. This paper describes parameter estimation of reliability model of the mechanical product based on adaptive linear neural network.

A. A model structure of the adaptive neural network

The adaptive linear neural network represents one of the most classical examples of an artificial neural network, being also one of the most simple in terms of the overall design. Model structure of the adaptive linear neural network is shown in fig. 2, which contains r input and s parallel neurons. Each element P_j (j=1, 2, ⋯, r) in the input vector P communicates with each output neuron through weigh matrix W, each output neuron obtains output vector A by a transfer function operation. The input vector of a transfer function is the net input vector of each neuron, whose result is the input vector P multiplied by weight matrix W. The output vector A is given by:

$$A_{S\times1}=f(W_{S\times r}P_{r\times1}+B_{s\times1})=W_{s\times r}P_{r\times1}+B_{s\times1}. \qquad (6)$$

Where f is a transfer function, s is node number of the input, r is node number of the output, and B is deviation vector.

A transfer function in fig. 3 is linear function. The relation between the input vector and the output vector is given by:

$$A_{S\times1}=f(W_{S\times r}P_{r\times1}+B_{s\times1}). \qquad (7)$$

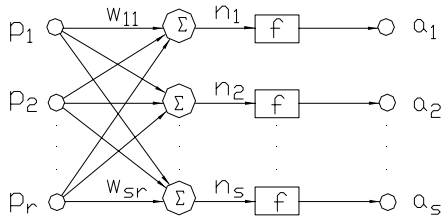


Figure 3. Structure of the adaptive linear neural network

B.Learning algorithm of the adaptive linear neural network

From above analysis, error function of the adaptive linear neural network is defined by:

TABLE III. RANDOM NUMBERS OF WEIBULL DISTRIBUTION

number	sample	number	sample	number	sample	number	sample	number	sample
1	3.7085	5	10.1229	9	14.7378	13	19.0040	17	23.8194
2	5.9020	6	11.5985	10	15.8436	14	19.7509	18	25.9925
3	7.5769	7	12.5008	11	17.2074	15	21.0040	19	30.9143
4	9.0431	8	13.8024	12	18.7587	16	22.8723	20	39.2141

TABLE IV. EXPECTED OUTPUT OF WEIBULL MODEL

number	expected output	number	expected output	number	expected output	number	expected output	number	expected output
1	-3.3612	5	-1.3408	9	-0.5873	13	-0.0259	17	0.5354
2	-2.4446	6	-1.1162	10	-0.4380	14	-0.1078	18	0.7048
3	-1.9534	7	-0.9214	11	-0.2965	15	0.2433	19	0.9114
4	-1.6099	8	-0.7469	12	-0.1597	16	0.3845	20	1.2074

TABLE V. MEAN TIME BETWEEN FAILURES OF TWENTY THE VIBRATORY ROLLERS

number	MTBF	number	MTBF	number	MTBF	number	MTBF	number	MTBF
1	310	5	514	9	688	13	951	17	1284
2	319	6	525	10	742	14	1085	18	1395
3	372	7	546	11	742	15	1261	19	1937
4	413	8	599	12	865	16	1282	20	1955

$$E = \frac{1}{2}(T - A)^2 = \frac{1}{2}(T - WP)^2 . \quad (8)$$

Where T represents target vector, namely output expected vector. According to (8), error surface formed by error function of the linear network has properties of parabolic surface. Thus, error function has minimum error value. Based on Widrow-Hoff learning rule, error value is close to minimum by adjusting weights and minimizing the sum of squares of errors. Error value depends on weights and target vector of network. Variation of weight is given by:

$$\Delta w_{ij} = -\eta \frac{\alpha E}{\alpha w_{ij}} = \eta (t_i - a_i) p_j . \quad (9)$$

Where, Δw_{ij} is variation of weight, and η is learning rate.

(9) also represents by:

$$\Delta w_{ij} = \eta \delta_i p_j . \quad (10)$$

Where, δ_i is the error value of the i-th output node.

$$\delta_i = t_i - a_i . \quad (11)$$

(10) is named Widrow-Hoff learning rule, also called δ learning rule, and least mean square error algorithm. According to Widrow-Hoff learning rule, Variation of weight of network is proportional to output error and input vector. Because it doesn't calculate differentiation, this algorithm is simple calculation, fast speed and high precision.

C. Numerical simulation

By method of random simulation, WEIBULL distribution data of parameters with $\beta = 2.5$ 、 $\eta = 30$ is obtained. These data is shown in table 3. Estimation of reliability given by middle rank is shown in table 4. For the above discussed adaptive linear neural network, program of neural network is written with MATLAB. Neural network have been trained and learned, and its result is given as follow: For WEIBULL distribution of parameters with $\beta = 2.5$ 、 $\eta = 30$, neural network is trained about 30000 times, and estimation of parameters β 、 η equals $\beta = 2.314$ 、 $\eta = 30.2459$. This result is identical to the result obtained with method of regression analysis, but it is better than the result of $\beta = 2.23$ 、 $\eta = 31.07$ obtained with probability paper.

VI. DETERMINING MEAN TIME BETWEEN FAILURE OF THE VIBRATORY ROLLER

A. Statistics of mean time between failures of the vibratory roller

Aimed at collection of using information of the vibratory roller, by analyzing the information, data of mean time between failures of the roller is obtained. It is shown in table 5.

Because reliability of the roller depends on reliability of units and parts, in fault times of view, faults proportion

hydraulic and dynamic system is much higher, accounting for 45.3% and 30.8% total fault individually. Faults of classis system and operation unit account for 15.9% and 8%. From analyzing fault reason, it is mostly caused by quality still and improper maintaining.

B. Recognition mean time between failure model of the vibratory roller based on BP neural network

A great deal of engineering practice and theoretic analysis prove: In general, reliability model of repairable system based on random process obeys exponential distribution and WEIBULL distribution. Data in table 4 are implemented normalization processing, selection of ten arbitrary data is regarded as one group of input vector, other data as another one group of input vector. The above two groups of data are regarded as input vector, which are input to trained BP neural network. According to the output results, we determine much suitable reliability model, and recognition results are given as follow:

y_1=0.0651 y_2=0.0002 y_3=0.0209 y_4=0.9242
y_5=0.0013 y_6=0.0042 y_7=0.0674 y_8=0.9662

According to the maximal membership principle, compared the output results with objective response, y_4=0.9242, and y_8=0.9662 are most close to objective response, thus recognition model BP neural network tallies with WEIBULL distribution, the result is in accordance with one obtained by mathematical statistical. So selection of WEIBULL distribution is regarded as reliability model of mean time between failures of the roller.

C. Parameters estimation of mean time between failures of the vibratory roller based on adaptive linear neural network

Based on adaptive linear neural, mean time between failures of the roller obeys parameter estimation of WEIBULL distribution. Density function of mean time between failures, corresponding, failure time distribution function and reliability function are given separately by:

$$f(t)=\frac{\beta}{\eta}(\frac{t}{\eta})^{\beta-1}e^{-(\frac{t}{\eta})^{\beta}} . \quad (12)$$

$$F(t)=1-e^{-(\frac{t}{\eta})^{\beta}} . \quad (13)$$

$$R(t)=e^{-(\frac{t}{\eta})^{\beta}} . \quad (14)$$

Where, β,η ($\beta,\eta>0$) are shape and scale parameter separately.

We select $y=\ln(-\ln R(t))$, $x=\ln t$, thus (14) is transformed into the following equation.

$$y=\beta(x-\ln\eta)=\beta x-\beta\ln\eta . \quad (15)$$

Middle rank is regarded as estimation R(t), namely,

$$R(t)=1-\frac{i-0.3}{n+0.4}(i=1,2,\cdots,n) . \quad (16)$$

Provided that n equals 20, mean time between failure t_i and estimation R(t) are in (16), and (x_i, y_i) are obtained. The input vector is X=[x_1 x_2 … x_n]$^{/}$, and objective vector is Y=[y_1 y_2 … y_n]$^{/}$. By the adaptive linear neural network, program of neural network is written with MATLAB. Parameters estimation of WEIBULL distribution is obtained as follow $\beta=2.001,\eta=1001.003$. From the above, density function of mean time between failure of the roller, corresponding failure time distribution function and reliability function are given separately by:

$$f(t)=(\frac{2.001}{1001.003})(\frac{t}{1001.003})^{1.001}e^{-(\frac{t}{1001.003})^{2.001}} . \quad (17)$$

$$F(t)=1-e^{-(\frac{t}{1001.003})^{2.001}} . \quad (18)$$

$$R(t)=e^{-(\frac{t}{1001.003})^{2.001}} . \quad (19)$$

According to the above function, the value of reliability index is calculated in different operation period of the vibratory roller. Aimed at operation state in different period, we shall take some technical and management measures to prevent failure or even accident from occurring.

V. CONCLUSION

On basis of description of the model structure of neural network and the traditional reliability model, the methods of recognition reliability model of the vibratory roller based on BP neural network and parameters estimation of reliability model based on the adaptive linear neural network are proposed. The neural network technique is introduced to analyze reliability model. According to this method, the reliability model and parameters estimation of the model could be quickly obtained if the life data of the known probability distribution was input to the model of the neural network. In practical applications, the method is easy to operate. Meantime, this method offers reference for other product reliability model. By this means, reliability model and parameter estimation of reliability model of mean time between failures of the vibratory roller are obtained.

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Heqing Li Hubei Province, China. Birthdate: February, 1969, Ph.D. candidate in Center South University. He graduated from Dept. Automobile & Mechanical Engineering, Changsha University of Science and Technology. His research interests include electromechanical integration and reliability system theory.

He is an associate professor of Dept. Automobile & Mechanical Engineering, Changsha University of Science and Technology.

Qing Tan Jiangxi Province, China. Birthdate: Feb, 1956, Ph.D. in Mechanical and Electrical Engineering. He graduated from Dept. Mechanical and Electrical Engineering, Center South University. His research interests include electromechanical integration and fault diagnosis.

He is a professor and doctoral tutor of Dept. Mechanical and Electrical Engineering, Center South University.