Research on the RBF Prediction Model of Attenuation Characteristics of Plane Shock Wave Pressure

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***Abstract* — Due to the existing researches on attenuation characteristics of plane shock wave pressure (PSWP) in solid materials didn't consider the influence of flyer' thickness on the attenuation characteristics of shock wave's peak pressure, and the attenuation model of pulse width didn't consider the effect of shock wave's rising time. This paper analyzes the influence parameters of PSWP and establishes the radial basis function (RBF) model predicting the attenuation characteristics of PSWP. The numerical simulation tests that flyers impact target boards under different conditions are simulated by using LS-DYNA software, and the samples to train and test the neural network are obtained. Based on the nonlinear mapping ability of neural network, the prediction model of attenuation characteristics of PSWP in oxygen-free copper is constructed with the training samples. By comparing the prediction values of testing samples based on the prediction model with the corresponding numerical values, the results show that the relative prediction errors of shock wave's peak pressure are less than 0.32%, the absolute prediction errors of shock wave's pulse width are less than 0.17us, which verifies the feasibility of the RBF prediction model and provides a theoretical guidance for the related research of attenuation characteristics of PSWP in solid materials.**

Keywords - plane shock wave pressure; neural network; attenuation characteristics; prediction model

I.INTRODUCTION

Plane shock wave pressure (PSWP) [1] has been widely used in synthesis of high energy density materials [2], explosive percussion [3] and the researches of dynamic characteristics [4]. For example, it is needed to know the attenuation characteristics of PSWP in solid materials to design the sample rooms to research the synthesis efficiency [5] of high energy density materials, and the shock initiation criterion [6] of condensed explosive is established by the energy arriving in the surface between shell and the explosive. So, it is of great significance to research the attenuation characteristics of PSWP in solid materials. In laboratory, it is usually used to produce PSWP by flying plate impact target board [7,8,**9**]. As far, the related scholars have carried out a lot of researches on the attenuation characteristics of shock wave's peak pressure in different materials. Tang, etc [10] researched the attenuation characteristics of shock wave's peak pressure in LY12-M aluminum. Cheng, etc [11] established the attenuation models of shock wave's peak pressure in aluminum foam material. Wang, etc [12] researched the attenuation characteristics of shock wave's peak pressure in C30 concrete by using the flyer, which was 10mm in thickness, to impact the target board of LY12 aluminum at the speed of 670 m/s. However, the exiting index attenuation models of shock wave's peak pressure were obtained under certain impact conditions, which didn't reflect the influence of flyer's thickness on the attenuation characteristics of shock wave's peak pressure.

The pulse width's attenuation model [13] doesn't consider the influence of shock wave's rising time. The rising time of shock wave in the interface between the flyer and target board is small, so it can be ignored. However, with the increase of propagation distance, the rising time of shock wave will increase, too. The relative errors between the actual values and theoretical calculation values of pulse width are larger and larger, at this situation, the influence of shock wave's rising time can't be ignored. Therefore, it is necessary to further study the attenuation characteristics of pulse width. Artificial neural network [14-18] has a very strong nonlinear mapping ability, which provides a solution for the difficulty to establish computational models accurately.

In this paper, the parameters affecting the attenuation characteristics of shock wave's peak pressure and pulse width are analyzed, and the RBF model predicting the attenuation characteristics of PSWP is established based on the principle of neural network theory. The tests that flyers impact target boards under different conditions are simulated by using LS-DYNA software, and the samples to train and test the neural network are obtained. Based on the nonlinear mapping ability of neural network, the RBF model predicting the attenuation characteristics of PSWP in oxygen-free copper is constructed with the training samples. Comparing the predictive values of testing samples based on the prediction model with the corresponding numerical values, the results verify the feasibility of RBF network model.

II.RESEARCH ON THE RBF PREDICTION MODEL OF THE ATTENUATION CHARACTERISTICS OF PSWP

A. The Structure and Algorithm of RBF Neural Network

1) The Structure of RBF Neural Network

RBF neural network is a three-layer feed-forward neural network [19-22], which includes an input layer, a hidden layer with radial basis function neurons and an output layer with linear neurons. As shown in figure 1 [19], hidden layer usually uses Radial Basis Function as excitation function and the radial basis excitation function is commonly Gaussian function, which is usually expressed as [19]:

$$R(x^q - c_i) = \exp\left[-(\left\|w1_i - X^q\right\| \times b1_i)^2\right] \quad (1)$$

Where $\left\|w1_i - X^q\right\|$ is the Euclidean distance, c is the center of Gaussian function, $b1_i$ is the thresholds of Gaussian function. $X^q = (x_1^q, x_2^q, ..., x_j^q, ..., x_m^q)$ is the q^{th} input data. $W1_i$ is the distance between the weight vector which is connected to the inputting layer and the every neuron in the hidden layer.

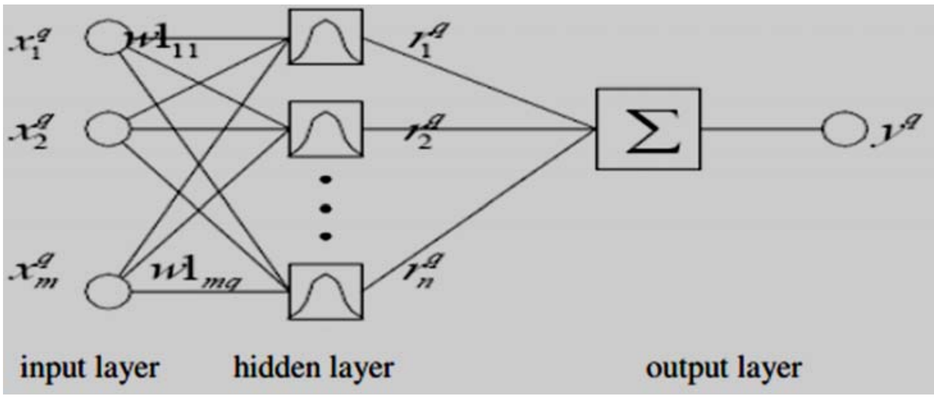

Fig.1 The Structure of RBF Neural Network

The i^{th} output of hidden layer neuron can be expressed as r_i^q [19]:

$$r_i^q = \exp\left(\sqrt{\sum_j (w1_{ji} - x_j^q)^2} \times b1_i\right) \quad (2)$$

The output of RBF neural network is the weighted summation of each hidden layer neurons' output and the excitation function uses pure linear function [19,20], so the q^{th} output layer neurons' output, which is corresponding to the q^{th} input, can be expressed as y^q [19]:

$$y^q = \sum_{i=1}^{n} r_i^q \times w2_i h \quad (3)$$

Where $W2_i$ is the distance between the weight vector which is connected to the outputting layer and the every neuron in the hidden layer.

2) The Learning Algorithm of RBF Neural Network

RBF neural network learning process has two stages [19,23,24]: first stage, self-organizing learning phase, this phase is the unsupervised learning process, solving the center and variance of the hidden layer base functions; second stage, tutor learning phase, this phase is solving weights which are between the hidden layer and output layer.

B. The Construction of RBF Prediction Model of the Attenuation Characteristics of PSWP

When the flyer's material and the target board's material remain unchanged, the parameters affecting the shock wave's peak pressure P_x and pulse width τ_x in the propagation distance x are: flyer's thickness D_f, velocity of flyer V_f, flyer's diameter H_f and target board's diameter H_t.

In order to obtain the attenuation characteristics of PSWP under different impact conditions, based on the RBF neural network theory, the five parameters: propagation distance x, flyer's thickness D_f, flyer's diameter H_f, velocity of flyer V_f and target board's diameter H_t are selected as the input parameters of the RBF model to forecast the attenuation characteristics of PSWP, and its output parameters are P_x and τ_x.

III. SIMULATION EXAMPLES

In order to identify the feasibility of the RBF model predicting the attenuation characteristics of PSWP, the numerical simulation method is applied.

Based on the LS-DYNA software, three simulation models are established. The relevant parameters of the first model: the flyer's thickness is 1cm, the flyer's diameter is 30cm, the target board's thickness is 15 cm, the diameter of target board is 30 cm, and the speed of flyer is 0.05 cm/us. The parameters of the second model: the flyer's thickness is 1 cm, the diameter of flyer is 30 cm, the speed of flyer is 0.10 cm/us, the diameter of target board is 30 cm, and the thickness of target board is 15cm. The parameters of the third model: the flyer's thickness is 2 cm, the diameter of flyer is 60 cm, the speed of flyer is 0.05 cm/us, the diameter of target board is 60 cm, and the thickness of target board is 30 cm. The materials of flyers and target boards are all oxygen-free coppers.

In order to reflect the dynamic unloading behavior in oxygen free copper [25], the flyer and target board adopt Johnson_Cook model and *Grüneisen* equation of state. The related parameters of the oxygen free copper are shown in table I and table II We use solid l64 unit to divide mesh, and take Lagrange algorithms. The contact between flyer and target board uses the eroding-surface-to-surface algorithm. Symmetry constraints are imposed on the symmetry surface between the flyer and target board, while fixed constraints are imposed around the target board. Due to the symmetry of the structure and load of the flyer and target board, it only simulates 1/4 of the model to reduce the computing time. The first model is shown in figure 2.

TABLE I PARAMETERS OF THE JOHNSON-COOK CONSTITUTIVE MODEL OF OXYGEN- FREE COPPER [11]

$A(\times10^{11}$Pa)	$B(\times10^{11}$Pa)	C	n	m	$\dot{\varepsilon}_0$ (us)
0.0009	0.00292	0.31	0.025	1.09	1e-6

TABLE II PATAMETERS OF *Grüneisen* EQUATION OF STATE OF OXYGEN- FREE COPPER

C_0(cm/us)	S_1	S_2	S_3	γ_0	A	E_0	V_0
0.394	1.49	0.0	0.0	2.02	0.47	0.0	1.0

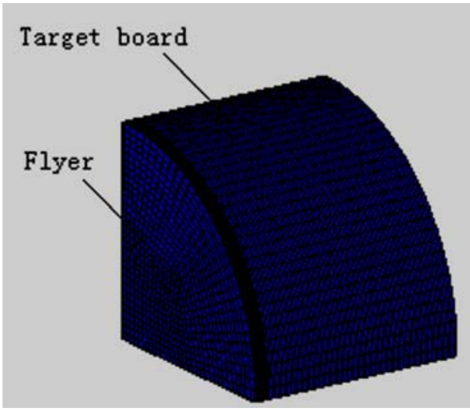

Fig.2 The First Model

IV. RESULTS AND DISCUSSION

A. *The Reliability Analysis of Simulation Results*

In order to identify the feasibility of the simulation results, the comparison values of PSWP between the simulation results and the theoretical results calculated by the models in Ref. 13 and Ref. 26 are shown in table III.

TABLE III THE COMPARISON RESULTS OF PSWP

		Theoretical Values	Simulation Values	Errors (%)
First model	Peak pressure (GPa)	9.63	9.58	0.52
	Pulse width (us)	3.66	3.73	1.91
Second model	Peak pressure (GPa)	20.92	20.90	0.10
	Pulse width (us)	2.86	2.91	1.75
Third model	Peak pressure (GPa)	9.63	9.60	0.31
	Pulse width (us)	7.32	7.45	1.78

From Table 3, the simulation values of the peak pressure and pulse width are in good agreement with the theoretical values. The relative errors of peak pressure are less than 1% and the relative errors of pulse width are less than 2%, which indicates that the numerical simulation results are reliable.

B. *Acquisition of Training Samples and Testing Samples of RBF Neural Network*

The samples, to train and test the RBF neural network, obtained by the numerical simulation models, are shown in table IVand table V.

TABLEIV THE TRAINING SAMPLES OF RBF NEURAL NETWORK MODEL

Serial number	D_f (cm)	V_f (cm/us)	H_f (cm)	H_t (cm)	x (cm)	P_x (GPa)	τ_x (us)
1	1	0.05	30	30	0	9.58	3.73
2	1	0.05	30	30	1	9.56	2.62
3	1	0.05	30	30	2	9.55	1.78
4	1	0.05	30	30	3	9.56	1.20
5	1	0.05	30	30	4	9.50	0.61
6	1	0.05	30	30	5	9.20	0
7	1	0.05	30	30	6	9.04	0
8	1	0.05	30	30	7	8.84	0
9	1	0.05	30	30	8	8.50	0
10	1	0.10	30	30	0	20.90	2.86
11	1	0.10	30	30	1	20.90	2.20
12	1	0.10	30	30	2	20.89	1.63
13	1	0.10	30	30	3	20.90	0.98
14	1	0.10	30	30	4	20.88	0.51
15	1	0.10	30	30	5	19.84	0
16	1	0.10	30	30	6	19.10	0
17	1	0.10	30	30	7	18.62	0
18	1	0.10	30	30	8	17.77	0
19	2	0.05	60	60	0	9.59	7.45
20	2	0.05	60	60	3	9.59	5.03
21	2	0.05	60	60	6	9.57	3.20
22	2	0.05	60	60	9	9.55	1.50
23	2	0.05	60	60	12	9.52	0
24	2	0.05	60	60	15	9.45	0
25	2	0.05	60	60	18	9.11	0
26	2	0.05	60	60	21	8.77	0
27	2	0.05	60	60	24	8.40	0

TABLE V THE TESTING SAMPLES OF RBF NEURAL NETWORK MODEL

Serial number	D_f (cm)	V_f (cm/us)	H_f (cm)	H_t (cm)	x (cm)	P_x (GPa)	τ_x (us)
1	1	0.05	30	30	0.5	9.58	3.10
2	1	0.05	30	30	6.5	8.96	0
3	1	0.10	30	30	1.5	20.91	1.82
4	1	0.10	30	30	6.5	18.76	0
5	2	0.05	60	60	2.0	9.59	5.67
6	2	0.05	60	60	16.0	9.35	0

C. The Training and Testing of the RBF Prediction Model

MATLAB neural network toolbox [14, 19] is used to design, train and test this RBF prediction model. Firstly, the samples can be normalized by the Eq. 4, so that each sample data can be located in [0, 1].

$$\hat{x}_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \qquad (4)$$

Where x_i is the actual value of sample, $x_{\min}$ is the minimum value of sample, $x_{\max}$ is the maximum value of sample, $\hat{x}_i$ is the normalized value of sample.

After the samples are normalized, we use the Gauss function and Linear function to train the RBF neural network. The training results of this RBF model are shown in figure 3.

It can be seen that the sum of the actual training errors' square is 8.43884e-5. The network training goal is 1e-4, and when the training times reach fourteen, the training target is approached.

Based on the Sim function, the prediction values of PSWP of the testing samples can be obtained. And the comparisons between the prediction values and simulation values of testing samples are shown in table □.

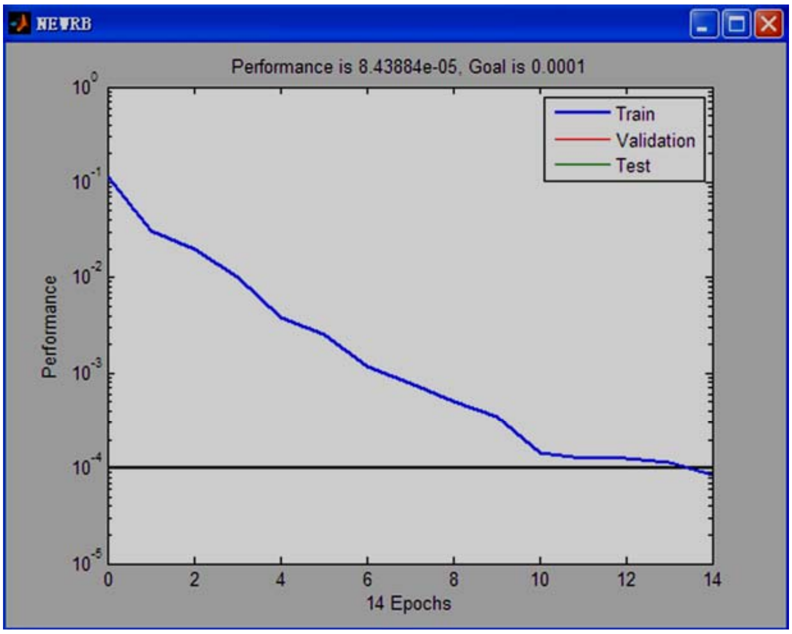

Fig.3 The Result of The Network Training

TABLE □ COMPARISONS OF PREDICTION VALUES AND SIMULATION VALUES

Serial number	Values of testing samples P_x (GPa)	Values of testing samples τ_x (us)	Predictive values P_x' (GPa)	Predictive values τ_x' (us)	$\left\lvert\frac{P_x-P_x'}{P_x}\right\rvert$ (%)	$\lvert\tau_x-\tau_x'\rvert$ (us)
1	9.58	3.10	9.57	3.15	0.10	0.05
2	8. 93	0	8.93	0.05	0	0.05
3	20.91	1.82	20.94	1.93	0.14	0.11
4	18.76	0	18.82	-0.03	0.32	0.03
5	9.59	5.94	9.57	5.77	0.21	0.17
6	9.35	0	9.34	-0.12	0.11	0.12

From table □, we can see that the relative errors between the prediction values and the simulation values of peak pressure are less than 0.32%, while the absolute errors between the prediction values and the simulation values of pulse width are less than 0.17us. It suggests that the RBF prediction model can predict the attenuation characteristics of PSWP in oxygen-free copper well, which demonstrates its feasibility.

V. CONCLUSION

This paper establishes the RBF model to predict the attenuation characteristics of PSWP in solid materials based on the RBF neural network theory. This prediction model contains all the influence factors of the attenuation characteristics of PSWP. After MATLAB training and forecasting, the RBF model achieves a good prediction effect, which provides a new way to predict the attenuation characteristics of peak pressure and pulse width in solid materials.

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