A NEURAL NETWORK APPROACH TO DETERMINATION OF LEADING DEBRIS CAUSED BY HYPERVELOCITY IMPACT ON WHIPPLE SHIELD

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ABSTRACT

Artificial neural network method was adopted to simulate the leading debris characteristics caused by space debris hypervelocity impact on Whipple shield. The shield spacing was included and the concept became an equivalent one for the whole secondary debris cloud, which is more realistic. A three-layer feed-forward back-propagation neural network was employed and sample data were taken from NASA hypervelocity impact test database on Whipple shield. The net was trained and agreed well with samples. The method of obtaining leading debris expression was discussed. And a kind of ballistic limit equation in term of critical rear wall thickness was obtained through neural network, which exhibit powerful prediction ability for shield failure or pass.

1. INTRODUCTION

Ballistic Limit Equations (BLEs), which describe the particle sizes that are on the failure threshold of a particular spacecraft component, are widely used to evaluate a particular shield's ability to withstand hypervelocity impact (HVI). A wide range of BLEs have been developed for the many kinds of shield structures based on HVI test results, numerical simulations, and analytical assessments, which is a cost-consuming task. Because of the complexity of HVI, the internal functional relationship between shield performance and shield configuration parameters is not clear to researches. As a result, the current BLEs are empirical regression equations setup to explain HVI experimental data. Though such functions can not be obtained directly, they could be approached by some kind of approximation method. Artificial Neural Network (ANN) is a good candidate as it is a powerful tool for function approximation. In fact, it has been shown that two-layer networks, with sigmoid transfer functions in the hidden layer and linear transfer functions in the output layer, can approximate virtually any function of interest to any degree of accuracy, provided sufficiently many hidden units are available (Hornik, 1989).

For multi-wall shields, a cost-saving leading debris approach can be employed, which obtains the characteristics approximation of leading debris (namely the most dangerous debris), caused by hypervelocity impact on first bumper and evaluate its damage potential for the next bumpers and rear wall in sequence. The characteristics of leading debris include its size, density, velocity and direction. Thus it can be determined whether the last wall will fail or not on the basis of single wall penetration equation. But what was ignored is the effect of shield spacing, which is an important parameter for any shield structure. As ANN is able to handle as many inputs as desirable, this problem can also be overcome. Furthermore, ANN has fine capability of generalization. It could give reasonable results for non-sample data as long as their inputs fall between the input ranges of network training.

A three-layer feed-forward Back-Propagation (BP) neural network was setup to determine the leading debris characteristics caused by space debris hypervelocity impact on Whipple Shield (WS). Sample data were taken from NASA JSC Whipple shield test database (Christiansen, 2003). The net was trained and agreed well with samples after training. The method of obtaining the expression of leading debris as well as a BLE in term of critical real wall thickness was also discussed.

2. BP NEURAL NETWORK

In BP network, the inputs are firstly propagated forward through the net, then the sensitivities according to the targets are propagated backward through the net, and finally the weights and biases are updated using the approximate steepest descent rule (Hagan, 1996). Therefore, the inputs and targets must be defined first of all.

The WS configuration as well as failure criteria were shown in Fig.1 (IADC, 2003). The independent variables are the projectile's diameter, density, velocity and incidence angel, the bumper's thickness and density, the spacing, the rear-wall's thickness, density and yield strength. There are 10 independent variables in total, but they needn't all be the inputs. To obtain the leading debris characteristics, the influence of target variables must be eliminated. So the rear-wall parameters can not be inputs and should be reflected from single wall penetration equation. The single wall penetration equation used is the modified Cour-Palais equation for

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the Apollo project by Burton Cour-Palais at JSC (Christiansen, 1991):

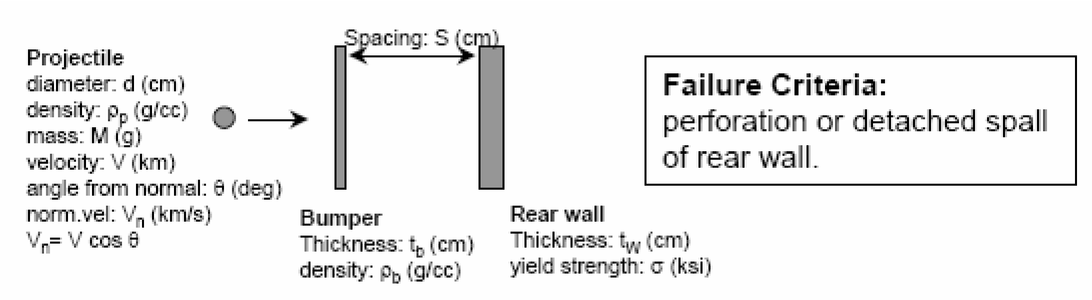

Figure 1. Whipple shield configuration and failure criteria (IADC, 2003)

For carter depth:

$$p = 5.24 d^{19/18} BH^{-0.25} \left(\frac{\rho_p}{\rho_t}\right)^{0.5} \left(\frac{V_n}{C}\right)^{2/3} \qquad (1)$$

For ballistic limit:

$$t_b = 1.8 p \qquad (2)$$

For spallation limit:

$$t_s = 2.2 p \qquad (3)$$

where:

p is crater depth on target (cm), BH is Brinnell hardness of target, C is speed of sound for target (km/s). The other symbols are identical with those in Fig.1.

In order to eliminate the influence of target variables, the inputs from the NASA WS test database must be selected as the same target material. The database varies over a large range of impact velocities and target parameters. The projectiles in these tests varied from 0.02 cm diameter to 1.9 cm diameter, impact velocities from 2 km/s to over 8 km/s, and impact angles from normal (0^o) to the surface to 75^o. Most of the tests used aluminum spherical impacts although glass, copper, and nylon projectiles are also represented in the database. The Whipple shields varied in this database from bumper thickness to projectile diameter (t_b/d) ratios of less than 0.05 to over 1.0, and S/d (shield spacing to projectile diameter ratio) from 3 to over 140. The targets in these tests did not contain MLI thermal blankets (Christiansen, 2003). The selected rear wall material was Al2024 since it takes the largest test amount. For Al2024 target, BH=120, ρ_t=2.79658, C=5.1368. Then the JSC equation in logarithmic form is

$$\ln t_s = 1.0556 \ln d + 0.5 \ln \rho_p + 0.6667 \ln V_n - 0.3571 \quad (4)$$

Eq. 4 can be regarded as a linear transfer function. The inputs are ln$d$, ln ρ_p, lnV_n of leading debris with output being lnt_s. And the weights and bias values are [1.0556 0.5 0.6667] and [-0.3571] respectively. Accordingly, other input variables should also be in logarithmic form. As most normal incidence angel in logarithmic form will yield negative infinite quantity, the incidence angel was combined with projectile velocity to represent the normal component of velocity. As a result, the total independent input variable is 6 in number, including the projectile's diameter, density and normal velocity, the bumper's thickness and density, and the shield spacing. Accordingly, the target or output should be the spallation limit of rear wall in logarithmic form lnt_s. Unfortunately, there is no data of crater depth on rear wall in the test database. Therefore, the rear wall thickness was multiplied by a factor to estimate the spallation limit. If the rear wall failed, the factor should be greater than 1, 1.2 used here; else the factor less than 1, and 0.8 was used.

For the inputs and output discussed above, a three-layer BP neural network was setup as shown in Fig.2. The whole network represented the WS, where the first and second layer representing the characteristics of leading debris and the third layer protection ability of single wall shield. Sigmoid transfer function was used in the first layer and linear type in both the second and third layer. The outputs from the second layer were to be ln$d$, ln ρ_p, lnV_n of leading debris, so 3 neurons were used in this layer. As there was only one output, the spallation limit of single wall lnt_s, 1 neuron was in the third layer, also the last layer of the entire network. The neuron number in the first layer can be changed to achieve different degree of accuracy, and 10 was used here. Linear transfer function was used in the third layer according to Eq.4. And the combination of sigmoid transfer function in the first layer and linear type in the second layer represented the approximation of unknown characteristic function of leading debris.

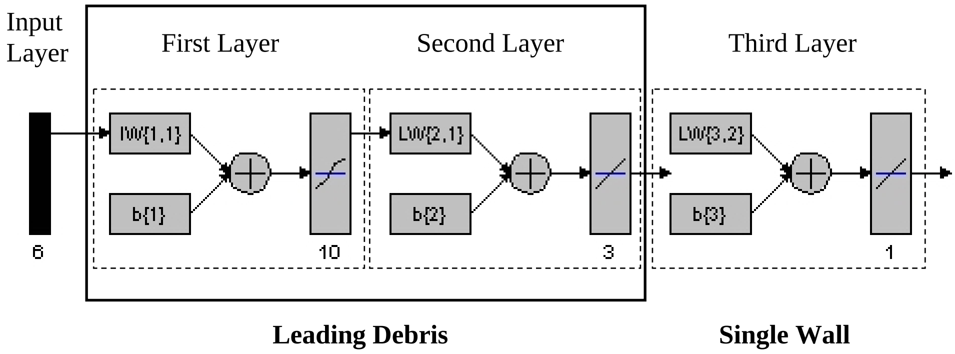

Figure 2. Thre- layer BP neural network configuration for Whipple shield

For the rear-wall selected test data, the network was trained and the result was shown in Fig.3 in term of the ratio of predicted critical rear wall thickness to that in test, as a function of normal component velocity of the tests. Shield failure is predicted when the thickness ratio is larger than 1.0, and no failure below the ratio=1.0 line. The targets were simulated well except some individual points, mainly due to the imaginary factor introduced. Most data points aligned with the ratio=1.2 and 0.8 line, which reflects the influence of the factor of 1.2 and 0.8 respectively. If the real crater depth in test were used, it is believed that the results would also be satisfactory.

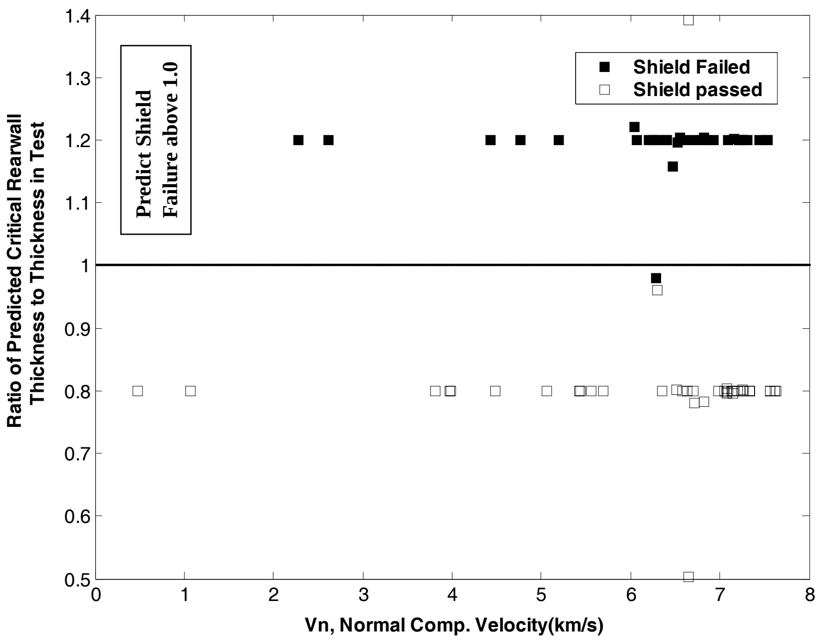

Figure 3. Result of BP neural network on Al2024 rear wall sample data

3. LEADING DEBRIS EXPRESSION

According to Fig.2 and Eq.4, the outputs of the second layer is the expression of leading debris in terms of its diameter, density and normal velocity, as a function of the 6 inputs. It should be noticed that the concept of leading debris here is not of the usual meaning, because it also contains the factor of shield spacing and the whole effect of the second debris cloud impacting rear wall. As a result, it can be considered as the equivalent leading debris for the debris cloud, which is more realistic and effective.

Generally, the trained results of the third layer would not be the same as those in Eq.4. Thus some transformation is needed in order to obtain the leading debris expression. Let $a^{\{1\}}$ denote the output matrix of the first layer, $w^{\{2\}}$, $b^{\{2\}}$ and $w^{\{3\}}$, $b^{\{3\}}$ denote the weight and bias matrix of the second and third layer respectively. Then the output of the entire network can be written in matrix form:

$$w^{\{3\}} \times \left(w^{\{2\}} \times a^{\{1\}} + b^{\{2\}}\right) + b^{\{3\}} = \ln t_s \qquad (5)$$

For the specification of Fig.2, Eq.5 can be extended as:

$$\sum_{i=1}^{3}\left\{w_i^{\{3\}}\times\left[\sum_{j=1}^{10}\left(w_{ij}^{\{2\}}\times a_j^{\{1\}}\right)+b_i^{\{2\}}\right]\right\}+b^{\{3\}}=\ln t_s \quad (6)$$

For one kind of rear wall material, Al2024 for example, the weights and bias values are fixed according to Eq.4 as below:

$$\tilde{w}^{\{3\}}=[1.0556\ 0.5\ 0.6667] \quad (7)$$

$$\tilde{b}^{\{3\}}=[-0.3571] \quad (8)$$

Keeping the total simulation results of network unchanged would yield

$$\tilde{w}_{ij}^{\{2\}}=\frac{w_i^{\{3\}}}{\tilde{w}_i^{\{3\}}}w_{ij}^{\{2\}} \quad (i=1,2,3;\ j=1,2,\cdots 10) \quad (9)$$

and

$$\sum_{i=1}^{3}\left(w_i^{\{3\}}\times b_i^{\{2\}}\right)+b^{\{3\}}=\sum_{i=1}^{3}\left(\tilde{w}_i^{\{3\}}\times\tilde{b}_i^{\{2\}}\right)+\tilde{b}^{\{3\}} \quad (10)$$

For simplicity, it can be made as

$$\tilde{b}_1^{\{2\}}=b_1^{\{2\}},\ \tilde{b}_2^{\{2\}}=b_2^{\{2\}} \quad (11)$$

Then it could be derived from Eq.10 that

$$\tilde{b}_3^{\{2\}}=\left(\sum_{i=1}^{3}\left(w_i^{\{3\}}\times b_i^{\{2\}}\right)+b^{\{3\}}-\sum_{i=1}^{2}\left(\tilde{w}_i^{\{3\}}\times\tilde{b}_i^{\{2\}}\right)-\tilde{b}^{\{3\}}\right)\Big/\tilde{w}_3^{\{3\}} \quad (12)$$

For different rear wall materials we would have different $\tilde{b}^{\{3\}}$ values but $\tilde{w}^{\{3\}}$ is the same as long as the JSC equation is employed as criterion of single wall shield ability. Meanwhile the weights and biases values in the second layer should be modified according to Eqs.9-12 with those in the first layer unchanged. As a result, the total simulation results of neural network were kept constant, which was guaranteed by the linear transfer function in the second and third layer. From these formulations the influence of the rear wall material was eliminated. And the expression of leading debris can be written in matrix form as:

$$ld=\tilde{w}^{\{2\}}\times a^{\{1\}}+\tilde{b}^{\{2\}} \quad (13)$$

or extended according to Fig.2 as:

$$ld=\sum_{j=1}^{10}\left(\tilde{w}_{ij}^{\{2\}}\times a_j^{\{1\}}\right)+\tilde{b}_i^{\{2\}} \quad (14)$$

When the expression of leading debris characteristics is established, it can be applied to multi-wall shield structure in the same manner. Each bumper can be represented by a two-layer neural network, which simulate the results of leading debris impact on bumper with the outputs being the inputs of the next network in sequence. Finally it can be determined whether the rear wall will fail or not according to single wall penetration equation.

4. BLE SIMULATION NETWORK

In a similar way a kind of BLE in term of critical rear wall thickness, instead of critical projectile diameter, can be obtained through ANN. It can also be regarded as a kind of sizing equation.

To this aim, the rear-wall's density and yield strength were also treated as inputs and the input number added up to 8. The whole database was trained and the results were shown in Fig.4. The data points of shield failure or pass were separated fairly well, except some individual points. Over 98% of the database was predicted accurately from a safety standpoint (failures predicted accurately), whereas the same figure of merit was 90% using the recently updated BLEs, which was shown in Fig.5 in reference to Christiansen, 2003.

5. CONCLUSION

Artificial neural network can be used to obtain the characteristics of leading debris caused by space debris hypervelocity impact on bumper. The Whipple shield can be simulated by a three-layer feed-forward back-propagation neural network, with the first two hidden layers representing the leading debris and the third layer describing single wall penetration equation. The expression of leading debris characteristics can be obtained through linear transformation to eliminate the influence of rear wall material, and be applied in multi-wall shield structure to predict the impact results. A kind of ballistic limit equation in term of critical rear-wall thickness, or size equation, can be simulated with neural network with all parameters included as inputs. The results indicated the powerful prediction ability of the method if the sample data were carefully selected to cover the whole range of shield structure parameters.

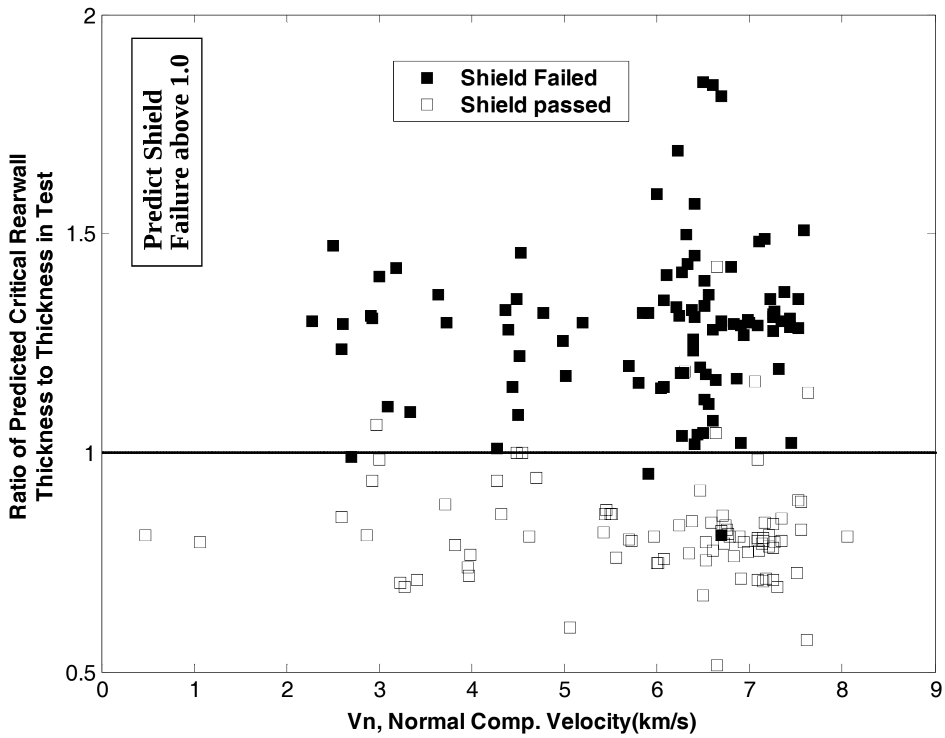

Figure 4. Predictions from ANN for about 200 different Whipple shield HVI tests

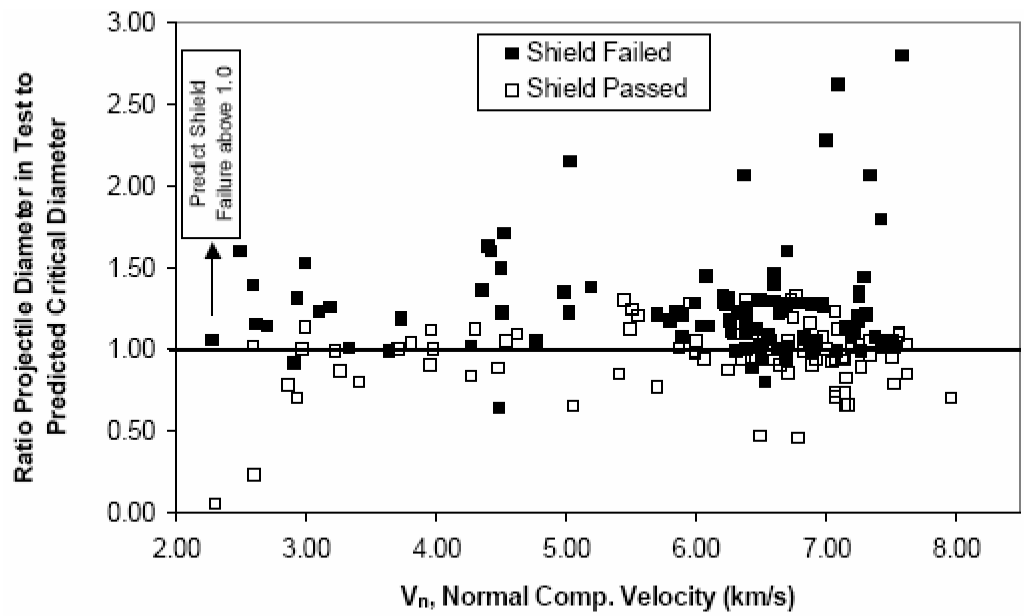

Figure 5. Predictions from updated BLEs for Whipple shield HVI tests (Christiansen, 2003)

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