Prediction of Explosion Heat of Aluminized Explosive Based on Artificial Neural Network

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***Abstract*—In this study, a three-layer artificial neural network(ANN) model was constructed to predict the explosion heat (Q) of aluminized explosive. Elemental composition was employed as input descriptors and explosion heat was used as output. The dataset of 24 aluminized explosives was randomly divided into a training set (17) and a prediction set (7). After optimized by adjusting various parameters, the optimal condition of the neural network was obtained. Simulated with the final optimum neural network, calculated explosion heat shows good agreement with experimental values. It is shown here ANN is able to produce accurate predictions of the explosion heat of aluminized explosive.**

Keywords-aluminized explosive; explosion heat; artificial neural network

I. INTRODUCTION

Since aluminized explosive has the characteristics of high explosion heat and temperature and post-detonation burning effect, it is widely used in rocket propellants, underwater munitions, air armaments, mine blasting, geological survey and even lunar development.

Explosion heat (Q) is one of the most important detonation parameters for aluminized explosive. To predict the explosion heat accurately is significant to the study of new aluminized explosive. There are usually two methods to calculate Q: (1) It can be obtained using Hess Law based on the detonation products. In this method, the detonation products are usually defined based on experience, which is difficult for a novice. And also the formation heat of reactants and products should be used, which must be calculated or measured beforehand. (2) It also can be calculated using eigenvalue of explosion heat of the components, which is demarcated by experiments. Based on the mass percentages of the components, explosion heat of aluminized explosive is obtained using additive method. However this method can not be used for the components of which eigenvalue of explosion heat has not been demarcated. So it is necessary to find a simple and comprehensive prediction method of explosion heat.

Recently, the ANN modeling technique has been used successfully in prediction of impact sensitivity [1-3] and detonation parameters of pure explosives [4]. In this paper, the ANN was employed to investigate the relationship between explosion heat and elemental composition of aluminized explosive (CaHbNcOdAle). The main goal of this study is to set up an ANN model of prediction of explosion heat.

II. ANALYSIS OF THE INPUT DESCRIPTORS

What is known as a critical aspect to construct an ANN model is the selection of suitable input descriptors. The descriptors should reflect the influencing factors of explosion heat as much as possible.

In simple terms, explosion heat, namely, constant volume combustion heat, refers to the heat released in combustion process of explosive or propellant. In this process, a redox reaction occurs between the combustion elements (C, H, N, Al) and the oxidation element (O). Simultaneously, it releases heat. Therefore, it is reasonable to represent explosion heat as a function of the elemental composition (a, b, c, d, e) of the aluminized explosive. That is to say, elemental composition should be selected as the input descriptor.

A close examination of experimental results shows that explosion heat has a a close correlation with the loading density (ρ). Hence, loading density is also a necessary input descriptor.

As discussed above, a,b,c,d,e and ρ were selected as the input descriptors to construct an ANN model.

III. ANN MODEL FOR EXPLOSION HEAT

ANN modeling, which originated about 60 years ago, is a parallel processing technique inspired by the desire to emulate human learning activity [5]. It is a highly self-organized, self-adapted, and self-trainable approximator, with high associative memory and strong non-linear mapping ability as well. By simulating the human neural system from micro-mechanism, ANN model can simulate complex and non-linear problems by employing a different number of non-linear processing elements, i.e. the nodes or neurons [6,7].

Usually, the network has one input layer, one hidden layer and one output layer. The input layer is consisted by the input descriptors. Information from the input layer is then processed in the course of the hidden layer, following output vector is computed in the output layer. In this study, the vector of input layer is X=(x1, x2,…,x6)=(a, b, c, d, e, ρ), and the output is Y=(y1)=(Q).

In developing an ANN model, the available dataset (Table 1) was randomly divided into two sets, a training set (17) and a prediction set (7). They were used for training of the network and verifying the generalization capability of the network, respectively. Various kinds of ANN approaches had been tried in this work. As a result, the linear ANN with Least Mean Square Error (LMSE) learning algorithm is the most accurate

ANN model to predict explosion heat. A schematic description of the linear ANN is given in Fig. 1.

TABLE I. PARAMETERS USED AS INPUT DESCRIPTORS

No.	a	b	c	d	e	Q [kJ/kg]
1	13.381	26.191	26.477	25.649	0	5770
2	12.512	23.992	22.961	22.961	0	5490
3	14.931	25.736	21.61	21.61	0	4690
4	15.211	29.172	26.589	25.882	0	5066
5	27.717	19.798	23.757	11.879	3.704	5307
6	21.557	15.398	18.478	9.239	11.111	6519
7	20.422	25.006	26.765	21.486	0	5020
8	27.554	27.206	25.354	6.599	0	5150
9	24.843	42.113	22.146	0	0	4850
10	13.107	26.417	20.529	20.529	0	6443
11	9.845	19.765	17.557	17.557	0	7046
12	6.888	13.776	13.776	13.776	14.815	8368
13	10.94	21.88	21.88	21.88	3.667	6357
14	11.021	22.042	22.042	22.042	1.481	5586
15	10.67	21.34	21.34	21.34	2.444	6006
16	10.089	20.178	20.178	20.178	3.926	6236
17	9.819	19.638	19.638	19.638	4.926	6415
18	8.874	17.747	17.747	17.747	7	6704
19	8.644	17.288	17.288	17.288	11.111	8317
20	11.345	22.69	22.69	22.69	3.704	6366
21	9.995	19.989	19.989	19.989	7.407	6760
22	8.644	17.288	17.288	17.288	11.111	7709
23	7.293	14.587	14.587	14.587	14.815	8299
24	13.478	26.696	25.653	25.392	0	5663

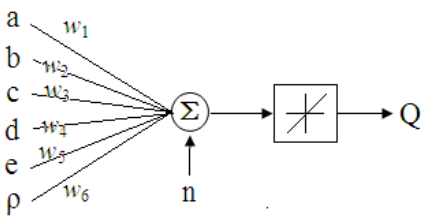

FIGURE I. THE STRUCTURE OF LINEAR ANN

IV. RESULTS AND DISCUSSION

As discussed above, a 5-9-1 ANN model was set up for predicting explosion heat of aluminized explosive. The predicted results by ANN model, experimental data and the calculated values by empirical equation of eigenvalue of explosion heat (EE) [8] for 7 aluminized explosives are presented in Table 2.

As can been seen in Table 2, the ANN model shows good ability for explosion heat of aluminized explosives prediction. The maximum error of predicted values is 3.83%. It is remarkable that the present ANN method is exceedingly simple, there is no need to use any experimental or calculated parameters. The input descriptors (a, b, c, d, e) can be easily obtained once the explosive formula confirmed.

TABLE II. COMPARISON OF P PREDICTED USING ANN MODEL AND MEASURED VALUES

No.	*Q* (Exp.) [kJ/kg]	*Q* (ANN) [kJ/kg]	Dev. (ANN) [%]	*Q* (EE) [kJ/kg]	Dev. (EE) [%]
1	5770	5549	-3.83	5770	-3.83
2	5490	5645	2.83	5793	5.52
7	5020	4981	-0.78	5211	3.80
11	7046	7040	-0.08	7386	4.83
13	6357	6321	-0.56	6357	0.00
23	8299	8479	2.17	--	--
24	5663	5524	-2.45	--	--
Note：-- Lack of necessary eigenvalue of explosion heat to calculate.					

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V. CONCLUSION

A well-trained ANN model was successfully used to predict explosion heat of aluminized explosives. Good agreement between the simulated values and the experimental values proved the utility of this method in a certain extent. The successful application also provided a simple and convenient way to predict other performances, such as detonation velocity and pressure, of composite explosives.

TABLE III. APPENDIX. EXPLOSIVE FORMULA

No.	Formula
1	HMX/94/NC/3/Binder/3
2	HMX/95/Binder/5
3	HMX/80/Binder/20
4	HMX/95.5/Binder/4.5
5	TNT/90/Al/10
6	TNT/70/Al/30
7	TNT/40/RDX/60
8	TNT/50/PETN/50
9	PETN/80/Binder/20
10	RDX/76/W/4/Al/20
11	RDX/65/W/1.5/G/1.5/Al/32
12	HMX/51/Al/40/Binder/9
13	HMX/81/Al/9.9/Binder/9.1
14	HMX/81.6/Al/4/Binder/14.4
15	HMX/79/Al/6.6/Binder/14.4
16	HMX/74.7/Al/10.6/Binder/14.7
17	HMX/72.7/Al/13.3/Binder/14
18	HMX/65.7/Al/18.9/Binder/15.4
19	HMX/64/Al/30/Binder/6
20	HMX/84/Al/10/Binder/6
21	HMX/74/Al/20/Binder/6
22	HMX/64/Al/30/Binder/6
23	HMX/54/Al/40/Binder/6
24	HMX/94/Binder/6

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