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# Prediction and evaluation of projectile damage in composite plates using the neural network–cloud model

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Composite plates are widely used in the aircraft manufacturing industry. The projectile damage of composite plates is affected by complex factors such as material, structure, impact velocity, and impact angle. A reliable method is needed for efficient structural health monitoring. In this paper, a composite plate damage prediction and evaluation model based on the cloud model and neural network is proposed; the five types of experimental characteristics are used as input parameters, and the depth and diameter of the damage area are used as output parameters to train the neural network–cloud model. This method transforms the quantitative data of impact damage of the composite plate into qualitative damage by introducing the cloud model, which makes the damage situation more intuitive. The results show that the accuracy of the prediction model is 97.23%, the accuracy of the evaluation model is 92.41%, and the comprehensive accuracy of the model is 89.85%. The composite damage prediction model has a good prediction performance.

## KEYWORDS

projectile damage, damage prediction, neural network, cloud model, machine learning, composite plates

## 1 Introduction

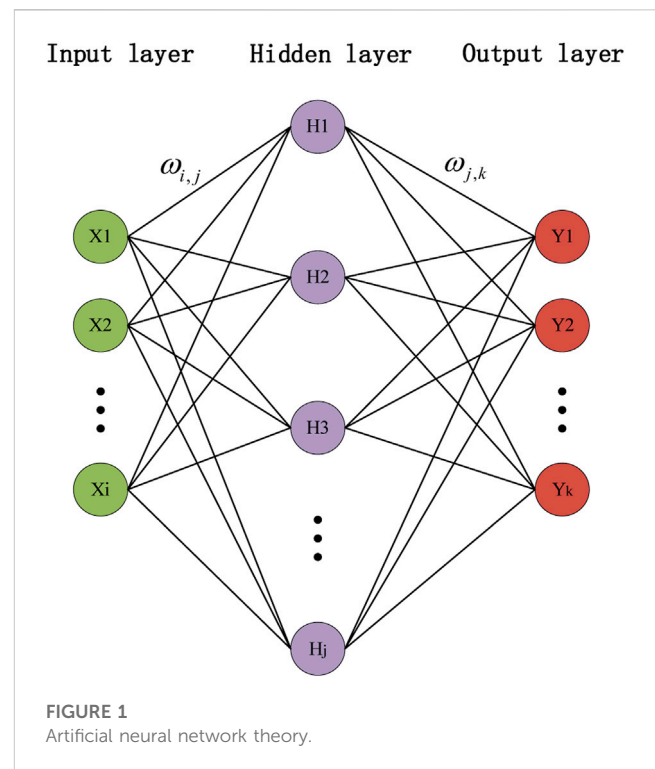
Composite plates have been widely used in the aircraft manufacturing industry due to its high strength and strong plasticity and have become the preferred structural material in newly developed aircraft structures (Dolati et al., 2014). At present, the utilization rate of composite plates in the airframe structure of Boeing B787 and Airbus A350, the representative models of two large civil airliners, has reached 50% and 53%, respectively (Dhanisetty et al., 2019). It can be said that the utilization rate of composite plates in the airframe structure has become an important symbol to measure the progressiveness and reliability of aircrafts (Oliveira et al., 2020). However, in the complex operating environment of aircraft, some external impacts such as bird impact, gravel, and hail, are often encountered (Anghileri et al., 2005). At this time, composite plates often show complex damage conditions.

In recent years, many studies have been carried out on the external impact of composite plates. Hosoi et al. (2017) studied the impact of damage on material properties through the falling weight impact test and three-point bending test and evaluated the damage

development within CFRP (carbon fiber-reinforced plastic). The results showed that the internal damage of the plate was mainly caused by internal delamination, and the impact tolerance of the panel could be improved by adding sandwich panels. Wei et al. (2020) carried out a pendulum impact experiment on CFRP composites and used a non-linear acoustic resonance method to detect their impact on fatigue damage. The results showed that the damage index increased slowly at the beginning of the impact cycle and rapidly increased when the fatigue life exceeded 70%. Hou et al. (2022) established the impact finite element model of waterjet-CFRP by studying the impact of high-speed water flow on CFRP plates. The results show that delamination is most likely to occur at the interface of adjacent layers with unequal dimensions in the plate structure, and the velocity and diameter of the waterjet have a significant influence on the damage of CFRP. Formisano et al. (2022) performed a low-velocity impact response of GFRP laminates with different thicknesses and conditions. Through the study of key characteristics, such as temperature and impact energy, it is found that the laminate will have lower indentation and delamination at low temperature, and the impact energy that can be resisted is also greater. Yang et al. (2022) used projectiles at different speeds to perform external impact experiments on curved GFRP laminates. By analyzing the residual velocity of the projectile and the energy absorption rate of the plate, the thickness required for the plate to achieve optimal performance was obtained.

The aforementioned research simulated the external impact through experiments, recorded the damage data of composite plates, and analyzed their damage development laws. These works are more suitable for judging whether the properties of composite plates are suitable for a certain engineering field. However, for the complex and changeable external working environment of the aviation industry, it is more important to timely judge whether the materials can resist the upcoming impact risk in the operation process. Until now, there are few theoretical studies on damage prediction and evaluation of composite plates. Therefore, in the field of composite damage, a model that can predict and evaluate in time according to the limited external information is needed.

Since the mathematical model of neurons was proposed in 1943, the research in this field has experienced immense popularity and decline, and various neural network-derived models have been proposed (Yang et al., 2021). Among them, the ANN (artificial neural network) is widely used because of its strong adaptive, self-organizing, and self-learning abilities in the fields of pattern recognition, intelligent robots, automatic control, predictive estimation, biology, medicine, and economy (Koopialipoor et al., 2019). The ANN has successfully solved many practical problems that are difficult to be solved by modern computers and has shown good intelligent characteristics. Maynard and Harris (2022) created 18 models of different systems by extracting accident data from official accident reports. By analyzing the convergence, universality, and stability of each model, the high-risk flight environmental factors are successfully predicted. Doğan and Demir (2022) took Turkey and China as the research objects and predicted the possibility of earthquakes within a specific time interval by



using the structural recursive network to capture spatial proximity and structural property.

In the aforementioned research, the neural network has been used in different engineering fields and has achieved good prediction results. However, the neural network is only a non-linear prediction of the research object, which will lead to deviation in the data results. Therefore, it is necessary to introduce an evaluation system that can tolerate errors in the evaluation process and realize quantitative and qualitative transformation so that the prediction results can be transformed into intuitive damage description. Gu et al. (2021) proposed a cloud model method for assessment of debris flow geological hazard risk. Through the calculation of a variety of evaluation factors, the risk level of debris flow is determined. Zhao et al. (2022) considered the natural fuzziness of safety and the volatility of safety level and then proposed an oil depot safety evaluation method based on cloud model theory. The reliability of the evaluation method was verified by taking the oil storage tank areas of four oil companies as examples. Through the aforementioned research, it can be found that in the field of composite damage, the combination of the cloud model and neural network can effectively predict and evaluate its damage status.

In this paper, an ANN based on the cloud model is established to realize quantitative calculation and qualitative evaluation transformation; five types of experimental characteristics are used as input parameters, and the depth and diameter of the damage area are used as output parameters to train the neural network–cloud model. Then, the model is analyzed to determine its prediction and evaluation effect. The results can provide theoretical support for damage prediction and evaluation of composite plates under projectile impact.

## 2 Methodology

### 2.1 Neural network–cloud model

The artificial neural network simulates the biological neural network from the perspective of informatics; the purpose of information processing is achieved by adjusting the connection mode within the network (Zhang, 2021). The ANN is one of the most popular neural networks, as an operation model; there are many nodes connected inside the neuron, and its structural principle is shown in Figure 1.

As shown in the aforementioned figure, the artificial neural network is composed of three layers: input layer, output layer, and hidden layer (middle layer). Each circle in the figure represents a neuron node. The number of input layer nodes  $X_i$  and output layer nodes  $Y_k$  is determined according to the number of known input parameters and target output parameters (Huang et al., 2022). The number of hidden layer nodes  $h$  is calculated using Eq. 1

$$h = \sqrt{i + k} + a, \quad (1)$$

where  $i$  represents the number of nodes in the input layer and  $k$  represents the number of nodes in the output layer. The value range of  $a$  is 1–10, and the final value needs to be determined according to the actual prediction results.

The connections among the layers in the network structure represent weights (thresholds), and the arrows represent the direction of signal transmission (Li et al., 2020). (The weights of the input layer and the hidden layer are represented by  $\omega_{i,j}$ , and the weights of the hidden layer and the output layer are represented by  $\omega_{j,k}$ ). The values of the  $n$ th hidden layer node and the  $m$ th output layer node are calculated using Eqs 2, 3

$$H_n = f \left( \sum_{i=1}^j X_i \omega_{in} \right), \quad (2)$$

$$Y_m = f \left( \sum_{j=1}^k H_j \omega_{jm} \right), \quad (3)$$

where  $l$  represents the  $l$ -th input layer node  $l = 1, 2, 3 \dots i$ ;  $n = 1, 2, 3 \dots j$ ;  $m = 1, 2, 3 \dots k$ .

In Eqs 2, 3, the activation function  $f(x)$  is a unipolar sigmoid function, as shown in Eq. 4

$$f(x) = \frac{2}{1 + e^{-2x}} - 1. \quad (4)$$

The neural network includes data flow forward propagation and error back propagation. The error output calculation follows the direction from the input to output. When the model output is inconsistent with the expected output, the error is back-propagated, and the weight (threshold) is adjusted to reduce the training error (Liu et al., 2014). Therefore, the error function needs to be introduced to achieve the optimal prediction of the network, as shown in Eq. 5

$$E = \frac{1}{2} \sum_{m=1}^k (y - Y)^2, \quad (5)$$

where  $E$  represents the error value,  $Y$  is the predicted value trained by the neural network, and  $y$  is the true value for verification.  $E$

reflects the prediction effect of the neural network model. When the prediction effect does not meet the requirements, the weight is adjusted (Liu et al., 2019). The weight adjustment function between the input layer and the hidden layer is shown in Eq. 6, and the weight adjustment function between the hidden layer and the output layer is shown in Eq. 7

$$\Delta \omega_{kj} = -\alpha \frac{\partial E}{\partial \omega_{kj}}, \quad (6)$$

$$\Delta \omega_{ji} = -\beta \frac{\partial E}{\partial \omega_{ji}}, \quad (7)$$

where  $\alpha$  and  $\beta$  represent the training rate, which reflects the neural network learning time.  $\alpha \in (0, 1)$ ;  $\beta \in (0, 1)$ .

We repeat the aforementioned training process, and the network stops training after the parameters (weights) corresponding to the minimum error are determined. The number of repetitions in the training process is called the training number. In the subsequent process, the information of similar samples is input into the neural network, and the network will process the information of non-linear transformation with the smallest output error.

The damage prediction data from the aforementioned process can be obtained, and then these data need to be converted between quantitative and qualitative transformations to facilitate evaluation (Cao et al., 2022). The cloud model based on probability theory can be used to study the relationship between fuzziness and randomness and complete the transformation from uncertain language description to quantitative expression (Gao et al., 2019). The principle is shown in Eq. 8

$$\mu: U \rightarrow [0, 1] \quad \forall x \in C \in U \quad x \rightarrow \mu(x), \quad (8)$$

where  $U$  is a domain,  $C$  is a qualitative concept, and  $x$  is a stochastic realization.  $\mu(x)$  represents the membership of  $x$  to  $C$ . The cloud models are evaluated by generating the cloud image through cloud generators; cloud generators are classified into forward cloud generator and back cloud generators (Liang et al., 2019).

The first step in the damage assessment phase is to convert the predicted experiment output parameters into three types of cloud digital eigenvalues. ( $Ex, En, He$ ). It is noteworthy that the diameter of the damage layer has a good effect when used to describe the surface damage of the plate, but its size is not directly related to the damage of the internal structure and cannot be used as a good basis for evaluating the damage degree. (Pérez et al., 2021). Therefore, in the damage assessment stage, the diameter of the damage layer is not included the determination of the damage degree. Since the original data involve three types of composite plates and each plate has different physical properties, such as thickness and size, in order to evaluate them at the same time, a unified reference is needed. Generally, the higher the degree of damage, the greater is the proportion of damage depth to the total thickness. Differences between plates can be ignored by using the depth ratio of the damage layer as an evaluation reference. The calculation process is as follows:

$$R = \frac{y}{h} * 100\%, \quad (9)$$

where  $y$  is the depth of the damage layer and  $h$  is the total thickness of the composite plates. In addition, the predicted damage depth

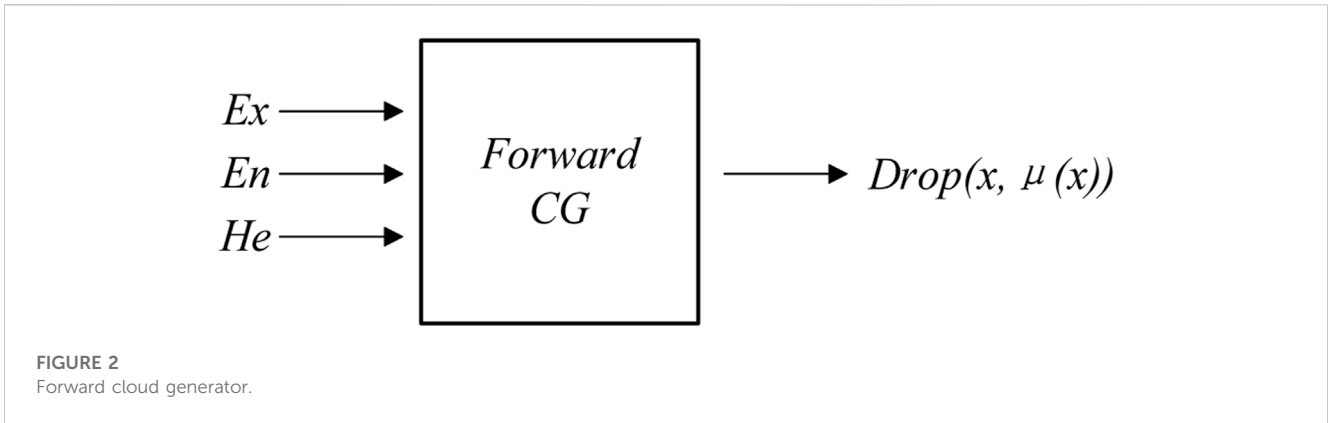


FIGURE 2  
Forward cloud generator.

ratio is obtained by neural network prediction. After comparing it with the real damage depth, the error between the two can reflect the accuracy of the model prediction; the calculation process is as follows:

$$A = \frac{1}{N} \sum_{i=1}^N |R_y - R_Y|, \tag{10}$$

where  $N$  represents the number of data for model training and  $R_Y$  and  $R_y$  are the values of true depth ratio of the damage layer and the predicted depth ratio of the damage layer, respectively. After obtaining the true depth ratio of the damage layer and the predicted depth ratio of the damage layer, the cloud digital eigenvalue of the experimental input data can be calculated using Eqs 11–13.

$$Ex_i = Y_i, \tag{11}$$

$$En_i = \frac{|Ex_i - y_i|}{3}, \tag{12}$$

$$He_i = k \cdot En_i, \tag{13}$$

where  $k$  is a constant, which affects the thickness of the cloud in the cloud image and can be adjusted according to the actual situation. After several adjustments, it is found that the cloud thickness is appropriate when  $k = 0.08$  (Wang et al., 2016).

The prediction model is established through the aforementioned process. In order to realize the damage assessment of composite plates, an evaluation model was constructed based on five kinds of experimental input parameters and three kinds of cloud digital eigenvalues. Then, the cloud droplet is generated based on the predicted ( $Ex, En, He$ ) (Xue et al., 2018). This process can be achieved through the forward CG (forward cloud generator). The principle is shown in Figure 2.

In the aforementioned figure,  $Ex$  is the spatial expectation value of cloud droplets in the cloud map, which can reflect the size of the prediction data.  $En$  represents the dispersion degree of cloud droplets and also reflects the deviation range between the predicted value and the true value.  $He$  is the degree of entropy dispersion, through which the thickness of cloud droplets can be observed (Zhao et al., 2020). We substitute the cloud digital eigenvalue into the forward cloud generator and generate cloud droplets via Eq. 14

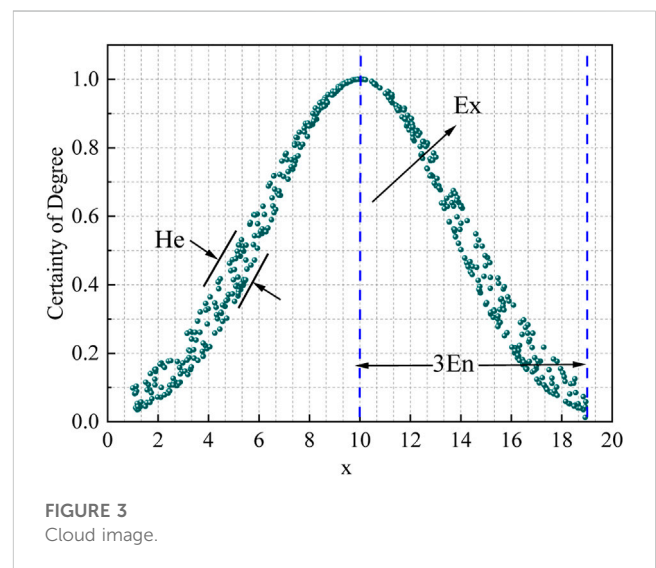


FIGURE 3  
Cloud image.

$$\mu(x) = \exp\left[\frac{-(x - Ex)^2}{2\lambda^2}\right], \tag{14}$$

where  $\lambda \sim N(En, He^2)$  and  $x \sim N(Ex, \lambda^2)$

We repeat the aforementioned process to generate a sufficient number of cloud droplets, and the cloud image can be formed (Zhou et al., 2016), as shown in Figure 3 (when the number of cloud droplets is below 1,000, some cloud image areas are blank. When the number is 1,000, the cloud image quality can be satisfied. This article sets to generate 1,000 cloud droplets)

## 2.2 Damage level

The damage level is very important for evaluating the predicted damage data. In this paper, the damage degree of composite plates is classified into four grades by referring to relevant literature (Xie et al., 2016): surface depression (Level I), substrate crack (Level II), interlayer delamination (Level III), and fiber breakage (Level IV). The range of each damage standard grade interval is expressed by the ratio of damage depth. The ratio corresponding to the four types of damage standard level

TABLE 1 Damage standard level.

Damage level	Value range	Description
I	(0,25)	The surface of the composite plate is sunken, and there is no obvious damage inside
II	(25,34]	Cracks appear on the surface of the composite plate, and the internal structure is relatively complete
III	(34,50]	Laminate separation and displacement in the composite plates
IV	(50,100]	The composite plate is completely penetrated, the internal structure is severely damaged, and the outer material is peeled off

TABLE 2 Standard cloud digital eigenvalues.

Level	Cloud digital eigenvalues		
	$E_x$	$E_n$	$H_e$
I	12.5	4.2	0.5
II	29.5	1.5	0.5
III	42	2.7	0.5
IV	75	8.3	0.5

where  $E_x^p$  and  $E_n^p$  are the expected values and the entropy of the  $p$ -risk level in the standard level, respectively, and  $M_p$  and  $N_p$  are the boundary values of the  $p$  level.  $\beta$  is adjusted according to the actual cloud dispersion to ensure proper cloud thickness. This paper assumes  $\beta = 0.5$ . After obtaining each damage standard grade, the number of cloud droplets can be calculated using Eq. 14, and then the standard cloud image is formed as shown in Figure 4. The degree of damage can be determined by comparing the cloud assessment image with the standard cloud (Xu and Xu, 2018).

### 3 Model verification and analysis

In this paper, 31 sets of damage data of composite plates are collected with reference to relevant literature (Jordan and Naito, 2014; Luo et al., 2020; Wang et al., 2022). Since this study aimed to obtain data that can feedback the damage situation through limited parameters before the experiment, which means that the experimental input parameters are easy to obtain and the output data intuitively describe the damage results. Based on the aforementioned considerations, the data involve five kinds of experimental input parameters and two kinds of experimental output parameters by screening the parameters. In addition, the training of the prediction model and the evaluation model allocate the data in a ratio of 7:3, but considering the small number of data samples, they are finally divided into three categories: test data (19 groups), validation data (eight groups), and evaluation data (four groups). The three composite plates are adopted, the main material of composite plate 1 is GFRP, and that of composite plate 2 and composite plate 3 is CFRP, and their thicknesses are 14 mm, 32 mm, and 3.6 mm, respectively. A total of 19 sets of test data are used as training samples of the neural network, as shown in Table 3.

The neural network fitting toolbox of MATLAB (which can solve fitting problem by using two-layer feedforward network) is used as the training tool, and the training samples are input to start the training. In the training process, the samples are randomly divided into three parts: training set, verification set, and test set. The training set is a data sample used for neural network model fitting. The model can be optimized by gradient descent of the training error, which has an important impact in determining the weight parameters of the built-in neurons. The validation set is a separate data sample used in the model-training process, which is used to adjust the parameters and feedback the model prediction effect. By using the validation set, the problem of the model can be found in time, and the generalization ability of the model can also be verified. The test set is used to evaluate the final generalization capability of the model. The data capacity ratio of the three types of samples is set

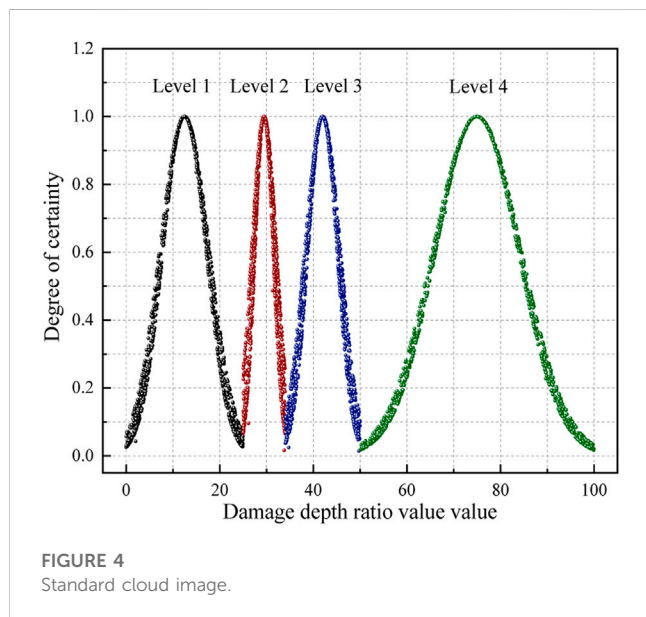


FIGURE 4 Standard cloud image.

intervals can be obtained by referring to relevant literature (Luo et al., 2020), as shown in Table 1.

The table contents show the range of damage depth ratios for each damage standard level. In order to establish a standard cloud image for reference and comparison based on the data in the table (Wu and Zou, 2020), the cloud digital eigenvalues are obtained via Eqs 15–17. The results are shown in Table 2.

$$E_x^p = \frac{M_p + N_p}{2}, \tag{15}$$

$$E_n^p = \begin{cases} \frac{E_x^2 - E_x^1}{3} & (p = 1) \\ \frac{E_x^p - E_x^{p-1}}{3} & (p \geq 1) \end{cases}, \tag{16}$$

$$H_e = \beta, \tag{17}$$



**TABLE 3 Composite damage test data.**

	Input					Output	
	Impact energy	Projectile diameter	Projectile mass	Impact velocity	Composite material	Depth of the damage layer	Diameter of the damage layer
1	1,023	7.52	2.85	813	1	10.7	10.4
2	476	7.52	2.85	528	1	10.8	11.5
3	549	7.52	2.85	617	1	10.1	6.9
4	658	7.52	2.85	672	1	9.4	11
5	278.1	35	20.8	163.5	2	9.5	10
6	289.4	35	21.3	164.9	2	7.71	8.65
	.				.		.
	.				.		.
	.				.		.
17	130.4	30	13	146	3	3.6	61.85
18	141.4	30	13	152	3	3.6	84.85
19	239.7	50	60	92	3	2.4	76.49

**TABLE 4 Composite damage validation data.**

No.	Input					Output	
	Impact energy	Projectile diameter	Projectile mass	Impact velocity	Composite material	Depth of the damage layer	Diameter of the damage layer
1	758	7.52	2.85	684	1	8.3	9.5
2	1,046	7.52	2.85	822	1	11.5	11.2
3	332.6	35	20.6	179.7	2	7.99	8.1
4	347.1	35	21	181.8	2	8.28	8.25
5	417.5	35	21	199.4	2	9.77	9.76
6	413.5	35	20.8	199.4	2	9.3	9.44
7	283.3	50	60	100	3	2.4	111.24
8	381.8	50	60	116	3	3.6	80.78

**TABLE 5 Damage layer depth ratio for validation data.**

No.	1	2	3	4	5	6	7	8
$R_y$	72.83	76.94	25.77	26.36	30.30	30.09	100.00	99.13
$R_x$	59.29	82.14	24.97	25.88	30.53	29.06	100.00	100.00

**TABLE 6 Cloud digital eigenvalue.**

No.	1	2	3	4	5	6	7	8
$E_x$	59.29	82.14	24.97	25.88	30.53	29.06	100.00	100.00
$E_n$	4.51	1.73	0.27	0.16	0.08	0.34	0.00	0.29
$E_e$	0.36	0.14	0.02	0.01	0.01	0.03	0.00	0.02

as 0.7:0.15:0.15. Then, the number of hidden layers is set. The range of the hidden layers can be determined as (3–13) according to Eq. 2. By comparing the actual values and predicted values under different layers, it is found that when the number of hidden layer nodes is 6, the error between them is the smallest and the model prediction effect is the best. In the toolbox, the advantages and disadvantages of each training algorithm are different. The Levenberg–Marquardt algorithm is chosen as the training algorithm in this paper. Although it will consume more running memory, the time it takes to train the model will be significantly reduced, which is important to improve the efficiency of neural network training. After setting the aforementioned parameters, the neural network model starts training. After setting the aforementioned parameters, the neural network model starts training. After inputting the eight sets of validation data shown in Table 4 into the model, the predicted values

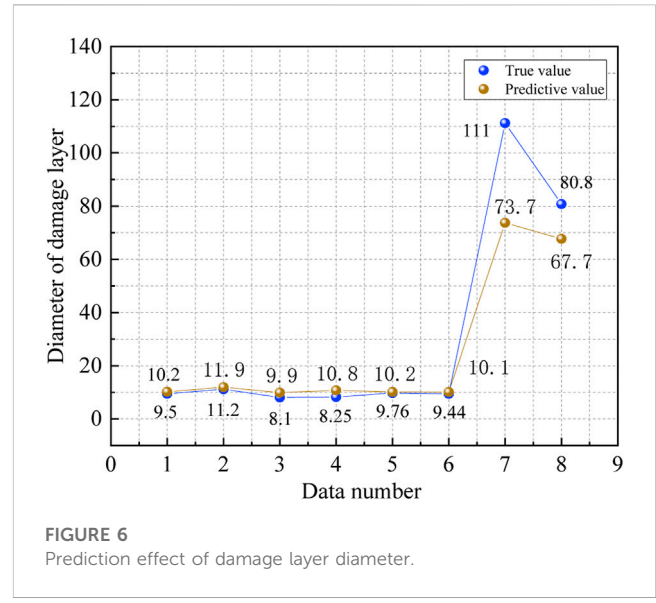
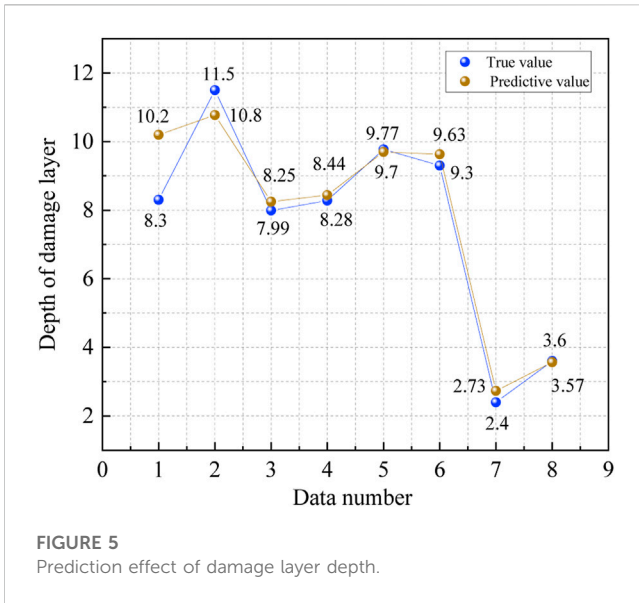


TABLE 7 Cloud model data.

No.	Input					Output		
	Impact energy	Projectile diameter	Projectile mass	Impact velocity	Composite material	<i>Ex</i>	<i>En</i>	<i>He</i>
1	758	7.52	2.85	684	1	59.29	4.51	0.36
2	1,046	7.52	2.85	822	1	82.14	1.73	0.14
3	332.6	35	20.6	179.7	2	24.97	0.27	0.02
4	347.1	35	21	181.8	2	25.88	0.16	0.01
5	417.5	35	21	199.4	2	30.53	0.08	0.01
6	413.5	35	20.8	199.4	2	29.06	0.34	0.03
7	283.3	50	60	100	3	100	0	0
8	381.8	50	60	116	3	100	0.29	0.02

of the validation data are compared. The detailed data of both are shown in Figures 5, 6.

Figures 5, 6 show the prediction effect of damage layer depth and damage layer diameter, respectively. The predicted values in both figures are close to the true values, which means that the trained neural network model has a good prediction effect and can be used to predict the damage degree of composite plates. In the eight sets of data, the prediction effect of composite material 3 is worse than that of composite material 1, and the prediction effect of composite material 1 is not as good as that of composite material 2, which is mainly caused by the number of training samples and the thickness of composite materials.

### 4 Damage evaluation

In order to realize quantitative calculation and qualitative evaluation transformation, the ratio of damage layer depth in

composite plates is calculated by Eq. 9, and the results are shown in Table 5.

Table 5 shows the true depth ratio of the damage layer and the predicted depth ratio of the damage layer. The accuracy of the prediction model is 97.23%, which can be calculated using Eq. 10. In order to realize the quantitative and qualitative conversion of the data and output the damage level reflecting the damage degree, the cloud digital eigenvalues of predicted data need to be obtained. Calculated using Eqs 11–13, the results are shown in Table 6.

The data in the table reflect the predicted value of the damage layer depth, the deviation between the real value and the predicted value, and the thickness of cloud droplet in the cloud image. The cloud digital eigenvalues in the aforementioned table are obtained based on the known experimental results, as shown in Table 7. Based on the data in Table 7; Eqs 15–17, the evaluation model can be obtained. Based on the trained evaluation model, four sets of evaluation data (each set of data contains five types of parameters) are input into it, and four sets of predicted cloud

TABLE 8 Evaluation data.

No.	Input					Output		
	Impact energy	Projectile diameter	Projectile mass	Impact velocity	Composite material	$E_x$	$E_n$	$H_e$
1	782	7.52	2.85	823	1	54.80	1.01	0.15
2	482.4	35	20.8	215.4	2	34.47	1.02	0.17
3	509.6	35	20.8	2,214	2	39.99	2.49	0.52
4	414.7	50	60	121	3	99.15	0.94	0.12

TABLE 9 Damage layer depth ratio for evaluation data.

No.	1	2	3	4
$R_y$	54.80	34.47	39.99	99.15
$R_y$	78.57	34.86	34.66	100

TABLE 10 Cloud droplet parameters.

No.	$\lambda$	$x$	$\mu(x)$
1	2.66	54.22	0.79
2	2.66	54.82	0.89
3	2.66	55.45	0.95
4	2.66	53.10	1.00
5	2.66	56.06	0.96
6	2.66	54.47	0.94
7	2.66	54.95	0.97
8	2.66	53.08	1.00
9	2.66	55.23	0.77
10	2.66	57.12	0.99
	.	.	.
	.	.	.
	.	.	.
998	2.66	55.52	0.65
999	2.66	56.12	0.96
1,000	2.66	53.12	0.43

digital eigenvalues ( $E_x$ ,  $E_n$ , and  $H_e$ ) can be obtained., as shown in Table 8. Based on the data in Table 8, the true value ratio and the predicted value ratio of the evaluation data are compared, and the results are shown in Table 9. The accuracy of evaluation data is found to be 92.41% by substituting the data of Table 9 into Eq. 10 for calculation, and the results show that the cloud model can be used to predict the cloud digital characteristics of the experimental data of composite plates. By further analysis of the data in Table 8 for damage assessment, the cloud droplets can be generated using Eq. 14. The first set of data in the table is taken as an example, and its cloud droplet parameters are shown in Table 10.

In Table 10, the independent and dependent variables of each cloud droplet are given. The damage layer depth ratio is used as the independent variable and the membership degree as the dependent variable. Taking no. 1 evaluation data as an example, the evaluation cloud image based on 1,000 cloud droplets is shown in Figure 7. In Figure 7,  $E_x = 54.8$ ,  $E_n = 1.01$ , and  $H_e = 0.15$  reflect the overall damage interval, the fluctuation range of damage depth, and the possibility of fluctuation of composite plates, respectively.

By comparing the cloud evaluation image with the standard cloud image, it is found that all cloud droplets are in damage level IV ( $50 < E_x \leq 100$ ). The proportion of cloud droplets in the damage standard level reflects the membership degree of damage level, so the membership degree of this group of experimental data to Level IV is 1. This means that under the experimental conditions of this set of data, the damage degree of the composite plates will be fiber breakage.

### 5 Conclusion

In this paper, a composite plate damage prediction and evaluation model based on the cloud model and neural network is proposed. A total of 31 groups of data related to composite impact damage experiments are collected, and the data involved five kinds of experimental input parameters (impact energy, projectile diameter, projectile mass, impact velocity, and composite plate) and two kinds of experimental

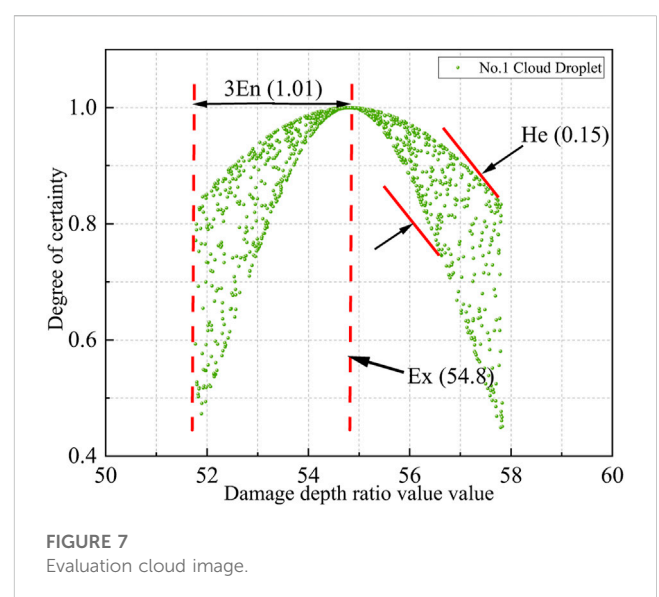


FIGURE 7 Evaluation cloud image.



output parameters (damage layer depth and damage layer diameter). Finally, the model is analyzed to determine its prediction and evaluation effect, and the conclusions are as follows.

- This paper proposes a computing model based on the cloud model and neural network, which provides a method for predicting and evaluating the damage degree of composite plates.
- The composite damage prediction model has good prediction performance, and the comprehensive accuracy of the model is 89.85%.
- It is found that the prediction error of composite plate 1 is up to 9.37%. The damage difference between composite plate 1 and composite plate 2 is not large, but the impact energy of the former is approximately 300% that of the latter, and the thickness is only 43.75% of the latter.

## Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material; further inquiries can be directed to the corresponding author.

## Author contributions

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

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## Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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