Research on Steam Cloud Explosion Overpressure Prediction Model Based on Improved BP Neural Network

Shengxiang Ma*, Xunxian Shi, Chenglong Yu, Bing Chen
China Academy of Safety Science and Technology, Beijing 100012, China

*Corresponding author e-mail: 474807303@qq.com, shixx@chinasafety.ac.cn, yucl@chinasafety.ac.cn, chenb@chinasafety.ac.cn

Abstract. In order to improve the feasibility and accuracy of steam cloud explosion overpressure prediction, a combination of factor analysis method and BP neural network method is proposed to propose an improved BP neural network prediction method. According to the original data of the main influencing factors of steam cloud explosion overpressure, the factor analysis method is used to reduce the dimensional data of the five steam cloud explosion overpressure factors, and obtain a common factor; replace the original with a common factor. As an input layer parameter of BP neural network, a steam cloud explosion overpressure prediction model is established by combining the factor analysis method with BP neural network method to predict the overpressure of steam cloud explosion. The improved BP neural network prediction method is verified by the example data. The final verification result is that the relative average error between the predicted and actual values of the 15 training samples is 2.51%, which proves that the improved BP neural network model with training has a good fitting effect. The relative errors of the five predicted samples were 0.77%, 1.34%, 2.07%, 3.96%, and 6.27%, both of which were less than 10%, which proved that the improved BP neural network prediction model has better prediction accuracy.

1. Introduction
Vapor cloud explosion is the main accident disaster in the production, transportation and storage of petrochemical, energy and other industries. Therefore, it is predicted that the vapour cloud explosion overpressure has become a hot spot for people to study, but it is very difficult to accurately predict the vapour cloud explosion. In the vapor cloud explosion, there are many factors that affect the explosion overpressure, such as reactivity, degree of restraint, concentration, volume, combustion heat, ignition energy, ignition position, etc. These factors interact with each other and are complicated and difficult to use. Mathematical formulas are accurately described. The same type of gas leaks to form a vapor cloud. Due to the different constraints, gas concentration and other conditions, the overpressure generated during the explosion may be very different, which makes the vapor cloud explosion overpressure difficult to obey the classical statistical law. For example, the TNT equivalent method of the vapor cloud explosion prediction model ignores various influencing factors. It is believed that the vapor cloud explosion overpressure is only related to the TNT equivalent of the vapor cloud. In
practical applications, the model has a large deviation from the simulation calculation of the vapor cloud explosion [1].

Therefore, how to predict the steam cloud explosion overpressure more effectively, quickly and accurately becomes a predictive technical problem that effectively prevents the occurrence of steam cloud explosion accidents. In recent decades, a large number of domestic and foreign scholars have successively launched research on the related technology of steam cloud explosion overpressure prediction. Li Yanchao and others based on the coupling mechanism of flame instability and explosion overpressure, established a pleated flame model and a turbulent flame model to theoretically predict the explosion overpressure in a closed combustion chamber [2]; Qin Yi et al. based on fractal combustion theory and related field experiments Based on empirical data, an explosion overpressure prediction model considering the flammable premixed gas explosion flame fold and turbulent flame propagation is established [3]; related scholars have found through research that flame instability will cause flame acceleration, resulting in explosive overpressure enhancement [4-6] Related scholars have carried out related research on explosive overpressure in confined space, and have a comprehensive understanding of its explosion overpressure and influencing factors [7-9]; Zhang Ruihua et al. used BP neural network principle and algorithm to construct and verify The feasibility of the steam cloud explosion overpressure model [10]. However, these methods have certain limitations in the verification research, because these prediction methods involve more prediction indicators, resulting in the prediction results often have low accuracy, slow convergence efficiency and poor reliability. The factor analysis method can simplify the relationship between the mutual predictive indicators and obtain the main influence factor, that is, the common factor, so that a larger number of common factors can be replaced by a smaller number of common factors.

Based on the principle of factor analysis, this paper proposes an improved vapor cloud explosion overpressure prediction method combining factor analysis and BP neural network method, which is to replace the original prediction index with the common factor obtained by the factor analysis method. The input layer parameters of the BP neural network structure reduce the number of input layer parameters of the BP neural network, simplify the structure of the BP neural network, and improve the iterative and computational efficiency and the prediction accuracy.

2. Application of Factor Analysis and BP Neural Network in Prediction of Vapor Cloud Explosion Overpressure

2.1. Data acquisition of main influencing factors of vapor cloud explosion overpressure

The main influencing factors of vapor cloud explosion overpressure: flammable gas reactivity (A1), space constraint degree of vapor cloud explosion (A2), flammable gas concentration (A3), vapor cloud volume (A4) and distance (A5). The raw data of the influencing factors are shown in Table 1 [10]. The reactivity of a gas has a lot to do with the possibility of explosion and the consequences of the explosion. The stronger the gas reactivity, the faster the reaction speed, and the greater the explosion overpressure generated during the explosion. Whether the flammable gas concentration is a stoichiometric concentration as an input value, if the gas concentration is a stoichiometric concentration or within a range of 1.1-1.5 times the stoichiometric concentration, the value is 1.0, otherwise 0.0. The degree of restraint of the space in which the vapor cloud is exploded is an important factor affecting the explosion pressure of the vapor cloud. If the vapor cloud is constrained, the gas cloud disturbance and turbulence can be increased, and the explosion pressure is increased. The larger the volume of the vapor cloud, the greater the explosion overpressure at the same distance. The same vapor cloud explodes, and the overpressure at different distances is different. The volume of the vapor cloud and the distance from the source of the explosion are also factors influencing the overpressure of the vapor cloud, so they are also used as network input factors.
Table 1. Impact factors raw data.

| Sample | A₁ | A₂ | A₃ | A₄/m³ | A₅/m | Explosion overpressure /kPa |
|--------|----|----|----|-------|------|-----------------------------|
| 1      | 1  | 0.3| 1  | 0.39270| 1.2  | 0.80000                     |
| 2      | 1  | 0.6| 0  | 0.39270| 0.8  | 1.92400                     |
| 3      | 0  | 1  | 1  | 2.91600| 10.7 | 2.47500                     |
| 4      | 0  | 1  | 0  | 32.00000| 24.0 | 2.02000                     |
| 5      | 0.5| 1  | 1  | 32.00000| 12.0 | 5.84000                     |
| 6      | 1  | 0  | 1  | 0.56549| 0.8  | 0.84139                     |
| 7      | 1  | 0  | 1  | 0.56549| 1.0  | 0.78603                     |
| 8      | 1  | 0  | 1  | 0.56549| 1.2  | 0.73359                     |
| 9      | 1  | 0  | 1  | 0.56549| 1.4  | 0.68398                     |
| 10     | 1  | 0  | 1  | 0.56549| 1.6  | 0.63715                     |
| 11     | 1  | 0  | 1  | 0.56549| 1.8  | 0.59298                     |
| 12     | 1  | 0  | 1  | 0.56549| 2.0  | 0.55141                     |
| 13     | 1  | 0  | 1  | 0.56549| 2.2  | 0.51236                     |
| 14     | 1  | 0  | 1  | 0.56549| 2.4  | 0.47574                     |
| 15     | 1  | 0  | 1  | 0.56549| 2.6  | 0.44145                     |
| 16     | 1  | 0  | 1  | 0.56549| 2.8  | 0.40938                     |
| 17     | 1  | 0  | 1  | 0.56549| 3.0  | 0.37940                     |
| 18     | 1  | 0  | 1  | 0.56549| 3.2  | 0.35137                     |
| 19     | 1  | 0  | 1  | 0.56549| 3.6  | 0.30045                     |
| 20     | 1  | 0  | 1  | 0.56549| 4.0  | 0.25499                     |

2.2. Factor Analysis of Influencing Factors of Vapor Cloud Explosion Overpressure

The raw data related to the main influencing factors of vapor cloud explosion overpressure were preprocessed by the factor analysis function of SPSS software. Based on the raw data in Table 1, a 20 x 5 matrix database is created. Select BP neural network input layer parameters as flammable gas reactivity (A₁), space constraint degree of vapor cloud explosion (A₂), flammable gas concentration (A₃), vapor cloud volume (A₄) and distance (A₅), application factor The analysis method reduces the dimensionality of the above input layer parameters, and replaces the original input layer parameters with the obtained common factors as the new input layer parameters of the BP neural network. The calculation process is as follows:

Data preprocessing. The SPSS software was used to calculate the variance contribution rate and cumulative contribution rate of each component (Table 2), the correlation matrix of each factor (Table 3) and the component matrix (Table 4). The factor with the cumulative percentage of the previous q eigenvalues greater than or equal to 80% is selected as the common factor. According to the results of Table 2, three common factors are selected.

According to the principle and method of the factor analysis method in Section 2, the SPSS software is used to calculate the component score coefficient matrix (Table 5) and the common factor matrix table (Table 6).
Table 2. Variance Contribution Rate of Each Component and Cumulative Contribution Rate Table.

| Ingredient | Initial Eigenvalue | Extract Square Sum Loading |
|------------|--------------------|---------------------------|
|            | Total Variance %   | Grand Total %             |
| 1          | 3.785              | 75.699                    |
| 2          | 0.695              | 13.900                    |
| 3          | 0.329              | 6.589                     |
| 4          | 0.180              | 3.610                     |
| 5          | 0.010              | 0.202                     |

Table 3. Related Matrix Table.

|       | A1    | A2    | A3    | A4    | A5    |
|-------|-------|-------|-------|-------|-------|
| A1    | 1.000 | -0.882| 0.402 | -0.707| -0.902|
| A2    | -0.882| 1.000 | -0.550| 0.759 | 0.793 |
| A3    | 0.402 | -0.550| 1.000 | -0.439| -0.510|
| A4    | -0.707| 0.759 | -0.439| 1.000 | 0.873 |
| A5    | -0.902| 0.793 | -0.510| 0.873 | 1.000 |

Table 4. Composition Matrix Table.

| Component Matrixa | Ingredient |
|-------------------|------------|
|                   | A1         | A2         | A3         |
| A1                | 0.953      |            |            |
| A2                | 0.927      | -0.882     | 0.402      |
| A3                | -0.917     | -0.550     | 1.000      |
| A4                | 0.883      | -0.439     | -0.510     |
| A5                | -0.629     | -0.510     | 1.000      |

Table 5. Matrix of Component Score Coefficients.

| Component Score Coefficient Matrix | Ingredient |
|------------------------------------|------------|
|                                    | A1         | A2         | A3         |
| A1                                 | -0.242     | 0.245      | -0.166     |
| A2                                 |            | 0.233      | 0.252      |

2.3. BP Neural Network Prediction Model Based on Factor Analysis

F1 in Table 6 is taken as the input layer parameter of the BP neural network, and the vapor cloud explosion overpressure is taken as the output parameter. The number of hidden layer neurons calculated by the traditional formula of the hidden layer neurons $l = \sqrt{mn}$ [11] and the empirical formula $l = 2n + 1$ [12] are substituted into the BP neural network prediction model, and the final result shows that when the hidden layer neurons are When the number is 3, the improved BP neural network has the best convergence and the highest accuracy, that is, the empirical formula is used to calculate the number of neurons in the hidden layer. It is finally determined that the topology of the BP neural network model is 1-3-1.

BP neural network toolbox in Matlab software was used to create BP neural network. One common factor was used as input layer parameter, vapor cloud explosion overpressure was used as output.
parameter, and tansig function and logsig function were selected as hidden layer neurons and input layer respectively. The transfer function of neurons uses the purelin function and the trainlm function as the output layer activation function and the BP neural network training function, respectively. The maximum number of training sessions for BP neural network is 150, the BP neural network training error is $1 \times 10^{-9}$, the BP neural network learning rate is 0.01, and the remaining BP neural network training parameters are default values. The first 15 sets of data samples of the common factor are used as training samples to learn and train the improved BP neural network prediction model. The training sample prediction results are shown in Figure 1. The average relative error between the predicted and actual values of the training samples is 2.51%. Therefore, the improved BP neural network prediction model has a good fitting effect on the training samples.

![Figure 1. Training Samples Prediction Results.](image)

**Table 6. Common Factor Matrix Table.**

| F1  |   |
|-----|---|
| 1   | -0.29526 |
| 2   | 0.42184 |
| 3   | 1.41093 |
| 4   | 3.25695 |
| 5   | 1.79343 |
| 6   | -0.50449 |
| 7   | -0.49542 |
| 8   | -0.48635 |
| 9   | -0.47728 |
| 10  | -0.46821 |
| 11  | -0.45914 |
| 12  | -0.45008 |
| 13  | -0.44101 |
| 14  | -0.43194 |
| 15  | -0.42287 |
| 16  | -0.41380 |
| 17  | -0.40473 |
| 18  | -0.39566 |
| 19  | -0.37752 |
| 20  | -0.35939 |
The last five sets of data samples of the common factor were used as prediction samples to test the prediction performance of the improved BP neural network prediction model. The improved BP model was used to predict and compare the vapor cloud explosion overpressure prediction samples. The predicted results are shown in Figure 2.

![Figure 2. Improved BP Model Prediction Sample Results Comparison.](image)

### Table 7. Comparison of Model Prediction Results.

| Sample Number | Forecast Result/kPa | Desired Result/kPa | Relative Error /% |
|---------------|---------------------|--------------------|-------------------|
| 16            | 0.40624             | 0.40938            | 0.77              |
| 17            | 0.37431             | 0.37940            | 1.34              |
| 18            | 0.3441              | 0.35137            | 2.07              |
| 19            | 0.28854             | 0.30045            | 3.96              |
| 20            | 0.23901             | 0.25499            | 6.27              |

The improved BP neural network model predicts the average relative error of the sample to be 2.882%. The improved BP neural network model predicts relatively small relative error and has good prediction accuracy of vapor cloud explosion overpressure. It is suitable for vapor cloud explosion overpressure prediction research.

### 3. Conclusion

1. Using the first 15 sets of training sample data to learn and train the improved BP neural network prediction model, and compare the predicted value with the actual value, the relative average error is 2.51%, which proves that the improved BP neural network model with training completion has good fitting effect.

2. Using the improved BP neural network prediction method for vapor cloud explosion overpressure prediction, the prediction results: the relative errors of the five prediction samples are 0.77%, 1.34%, 2.07%, 3.96%, 6.27%, respectively, less than 10 %, which proves that the vapor cloud
explosion overpressure prediction method based on factor analysis and BP neural network is finally feasible and the prediction has good accuracy.

Acknowledgments
The authors would like to thank China Academy of Safety Science and Technology. This work is supported by Basic research fund of China Academy of Safety Science and Technology (Grant no. 2019JBKY09 and 2019JBKY08)

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