Analysis on Gas Disaster Evaluation Method of Coal Mine

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Abstract
Gas disasters are the main threat to coal production safety, to achieve stable and reliable security situation prediction is very important. Effective analysis of coal mine production safety status is of great significance to coal mine safety production. This paper uses the gas monitoring data of the working face of Shendong mining area as the sample, by building a prediction model and using a mathematical model method to determine the safety level of the coal mine area. The prediction of the gas emission law of coal mining face is realized to predict the gas data trend, use the data to measure and use the root mean square error and average absolute error indicators to measure the accuracy of the gas emission prediction results, verify that the prediction accuracy rate can reach 98.21%. The establishment of a coal mine gas disaster prediction model is of great significance for the avoidance of coal mine risks. Predicting possible coal mine gas disasters in advance can better ensure the safety of coal mine operations and reduce the property and life and property losses of mine and underground personnel minimum.
Index Terms: Coal mine Gas disaster, Data Fusion, Time series prediction, Gas data, Situation assessment.

1. Introduction

With the gradual complexity of the production process of the coal industry, the diversification of products and the expansion of production scale, there are more and more potential safety hazards in coal operations; at the same time, due to the particularity and complexity of the coal production process, coal mines, the problem of safety production runs through the whole process. While local coal industry is developing rapidly, the severe safety production situation in coal mines is still the primary factor hindering the development of coal mine production.

At present, the coal industry pays more and more attention to safety production. The original traditional coal mine safety system has been unable to meet the new production technology. It is very important to strengthen the theoretical basis of coal mine disaster prevention and control and improve the technical level of early warning and prevention. Integrate safety production management by means of information technology, use the principles and methods of systems engineering to conduct qualitative and quantitative analysis, evaluation and prediction of safety problems in coal mining areas, and use the management concept of risk prediction in daily safety production management, and take appropriate comprehensive measures to control it in time to minimize the possibility of accidents, so as to achieve the purpose of safe production. Driven by the continuous development of mine safety theory and technology, the scientific management of coal safety and the effective prevention of accidents have become a major subject in the field of coal mine safety research. Safety production has become the key to the coal mine production process [8]. The technology and theory of safety incidents play an important role in the development of the entire coal industry. Only by ensuring the safe development of the industry and realizing a scientific management model can the rapid development of the local coal industry and the world be better promoted. This is also a part of the coal industry key research directions. Furthermore, the effective monitoring of the disaster-causing factors in coal mines and the accurate prediction of the catastrophic trend are the key means for the prevention and control of coal mine accidents [24]. Due to the complex correlation of disaster-causing factors in coal mine safety, the analysis and research of coal mine safety early warning method based on data fusion has important theoretical significance.

The main purpose of this research is to predict the trend of gas concentration in a short time and predict the possibility of gas explosion accidents by reading data, processing data, and analyzing data.

With above mentioned, the main objective of this study is to fully grasp the real-time parameters of coal mine harmful gas and production status data in a comprehensive and timely manner, and to achieve stable and reliable safety situation prediction, and also a key step to realize safety early warning data analysis.

2. Methodology

This paper uses the gas monitoring data of the working face of Shendong Shangwan mining area as the sample, by building a prediction model and using a mathematical model method to determine the safety level of the coal mine area. In this study, several teachers in the Coal Mine Safety Research Institute also participated in the data collection and analysis, in which a variety of gas concentration detection sensors were used to detect the gas data concentration.

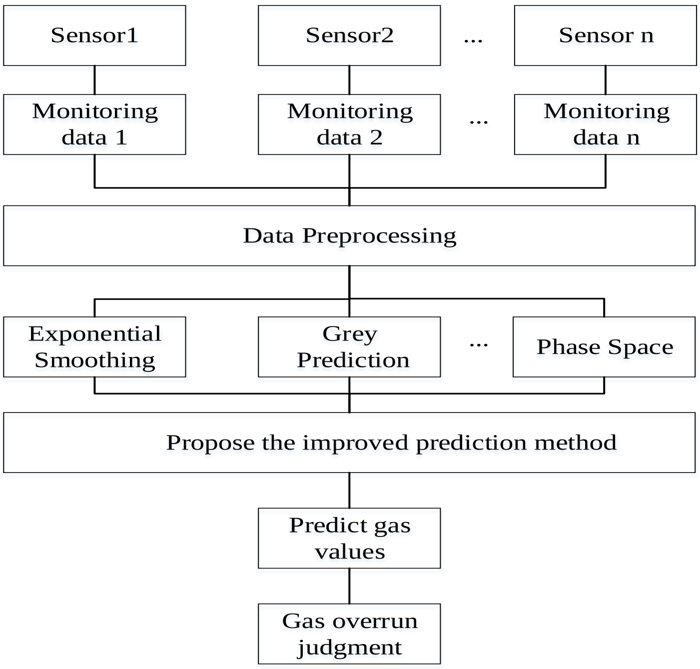


Fig 1. The methodology of the Gas Disaster Evaluation analysis

Risk prediction of the possibility of gas disasters is an indispensable part of mine safety production. After preprocessing the data collected by sensors, a time series more suitable for data analysis is generated. Based on several time series prediction methods, an improved method is proposed. The gas disaster prediction model, by using the gas data of Shangwan Coal Mine for model verification, is expected to achieve a more accurate prediction effect and determine whether the gas exceeds the limit.

A. Data Collection

The occurrence of gas disaster is a complex process. If the data obtained by a single sensor is abnormal, the original data will not completely fit the measured data, which will lead to inaccurate prediction. Data from multiple sensors are selected as relevant data in the area where the gas sensors are located to jointly act on the regional safety evaluation, to verify the above proposed model and to determine whether the results are more accurate.

In this paper, the gas concentration data of an upper corner monitoring point of the mine from August 3, 2019 to August 31, 2019 are selected for modeling. The sensors detected every 5 minutes a day, and the maximum gas concentration, minimum gas concentration and average gas concentration at that time are provided. There are 14 average measurement points in each hour, and the measurement points are at 0, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50 and 55, respectively. In addition, the maximum, minimum and average values of each hour are also provided.

B. Data Preprocessing

Firstly,the data source is analyzed statistically and preprocessed. There are missing values and abnormal values in the data. A large number of missing values will affect the data prediction, so the missing values are filled in first. The main steps of the method are as follows: based on the multiple periods of the data series, with the peak value of the period as the weight, the weighted mean value is calculated to fill the null value for different periods. After filling in the data series, the time series is more complete, which can be used for further prediction though algorithms. If the missing values are not filled, then the time period is not a complete period, which will definitely influence the model prediction results.

At first, the period of the time series is calculated. According to the period calculated from the data, the mean value of the historical data in different periods is calculated. For different periods, the peak value of each period was selected and weighted with the historical mean of the original calculation to obtain the filling value. The weight mean was filled and then further tested. Repeat the above steps until the error is reduced to 0.2, stop the loop iteration, and the missing data is filled. For the treatment of outliers, the definition of normal distribution states that the probability of being more than 3δ away from the average value is $P(|x-\mu|>3\delta)\leq 0.003$, which is a very rare event. Therefore, when dealing with general data, it can be considered that there is no sample whose distance exceeds the mean value by 3δ. Therefore, in this model data processing work, when the data value exceeds the mean value of 3δ , this value can be considered as an outlier, and the value of 3δ can be directly used to replace the outlier.

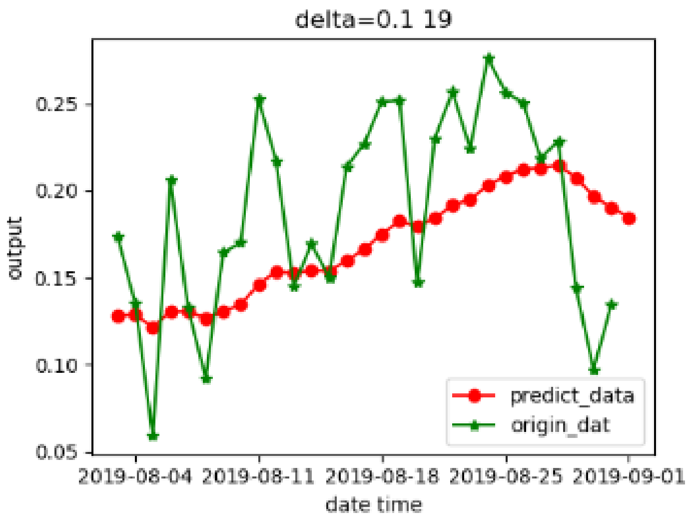
3. Result and Discussion

According to the data, it is found that the gas emission data has a certain trend, but the seasonality is not obvious, so the exponential smoothing method is selected for the prediction. The smoothing coefficient of exponential smoothing method, ranging from 0 to 1, is the weight of observed values in different periods in the predicted value. It is subjective, and its value is affected by the real value at the previous moment. Generally, the value can be determined according to the fluctuation of time. When the fluctuation is small, a smaller value will be taken. When the fluctuation is large, a larger value will be taken.

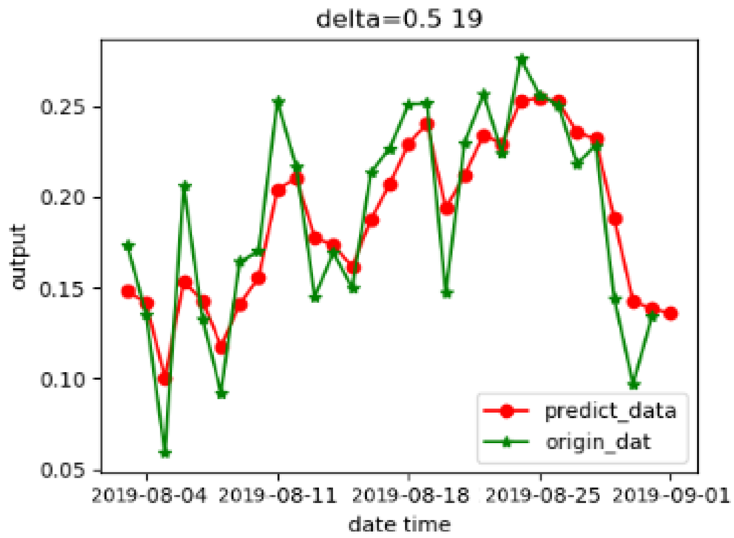
At present, trial algorithm and empirical judgment method are commonly used to select, and the empirical judgment method is used to preliminarily determine the value range of , and then different values of are selected to calculate the prediction error. The value of the minimum prediction error is selected as the final model parameter value. The selection of the smoothing coefficient is mainly based on the followings: when the smoothing constant approaches 1, the recent actual value of the data has an effect on the overall smoothing value, which decreases very fast; When the smoothing constant approaches 0, the effect is just the opposite. In order to select a better effect, the smoothing coefficients are respectively 0.1,0.5 and 0.8. The optimal coefficient value is selected by comparing the results, and the optimal coefficient is used to train data from August 4 to August 31. By comparison, it is found that when the smoothing index is 0.8, the prediction effect of the data is better, and both the periodicity and the prediction accuracy are the closest to the original data.

Table 1. Smoothing coefficient values

Fluctuations and trends of time series	α value
Trend is stable	0.05~0.20
There was slight fluctuation and no long-term trend of change	0.10~0.40
There was slight fluctuation and no long-term trend of change	0.60~0.80
There is a sharp upward or downward development trend	0.80~1.00



(a)



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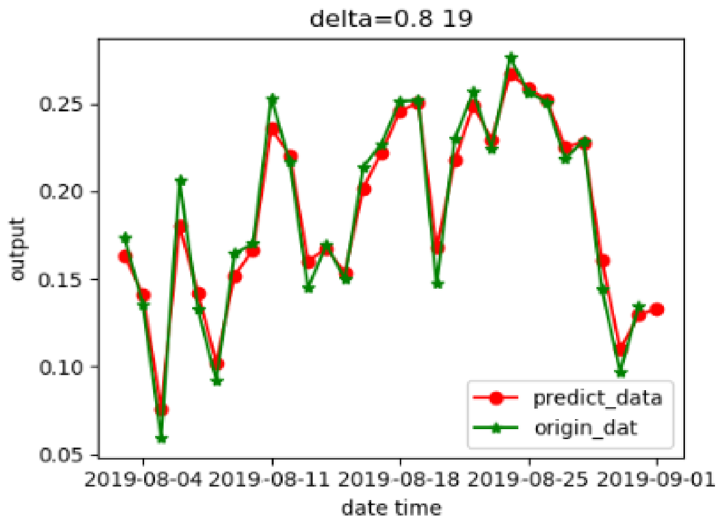


(c)

Fig 2. Line chart of perdition when the exponential smoothing coefficient is 0.1, 0.5 and 0.8

A. Grey Prediction of Gas Concentration

Although the exponential smoothing algorithm can predict the data, when the value of α is 0.8, the most appropriate exponential smoothing algorithm results showed that the data and the original data still have a certain error, so other algorithms should be used to model and optimize. The gray prediction algorithm was selected to predict the data. Because gray level prediction is established through the calculation of the first-order ordinary differential equation, it is also called the first-order gray model. When the model test results of the original sequence are not ideal, the residual correction results can be carried out to achieve better prediction effect and improve the prediction accuracy of the model.

B. Phase Space Reconstruction Method for Gas Concentration

The original time series is processed. The principle of phase space is to reconstruct the original time series into a new phase space and select the embedded dimension. When the selected dimension is high enough, equivalent data can be recovered[29].The main idea is to find the best dimension and delay time, and then realize the prediction of the data.

The original sequence is

$$[x(1), x(1+\tau), \dots, x(k), x(k+\tau), \dots, x(l)]^T \tag{1}$$

Calculate the delay coordinates

$$X(k) = \{x(k), x(k+n\tau), \dots, x[k+(l+n-mn)\tau]\}^T \tag{2}$$

The final generated phase space

$$\tilde{X}(k) = \begin{bmatrix} x(k) & x(k+n\tau) & \cdots & x[k+(l+n-mn)\tau] \\ x(k+n\tau) & x(k+2n\tau) & \cdots & x[k+(l+2n-mn)\tau] \\ x[k+(m-1)n\tau] & x(k+mn\tau) & \cdots & x(k+l\tau) \end{bmatrix} \tag{3}$$

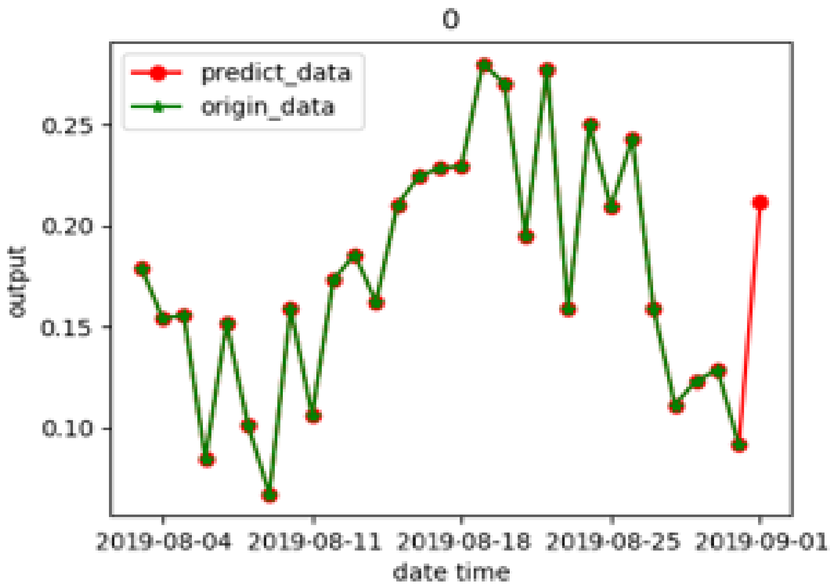
C. Propose the Improved Prediction Method

After the above data testing, it is found that the three prediction methods can predict the gas concentration change at each time node in the specified time interval, but each model has different accuracy, and each has its own advantages and disadvantages. The three algorithms are combined in a certain rule, and the optimal model is selected through model verification. The optimal combination prediction is a way to realize the construction of the objective function by maximizing a certain accuracy criterion or removing a certain error criterion under certain normalization conditions, such as the normalization of the weight coefficient, so as to calculate the prediction effect of different combination prediction. The mathematical programming model can be used to express the optimal prediction combination：

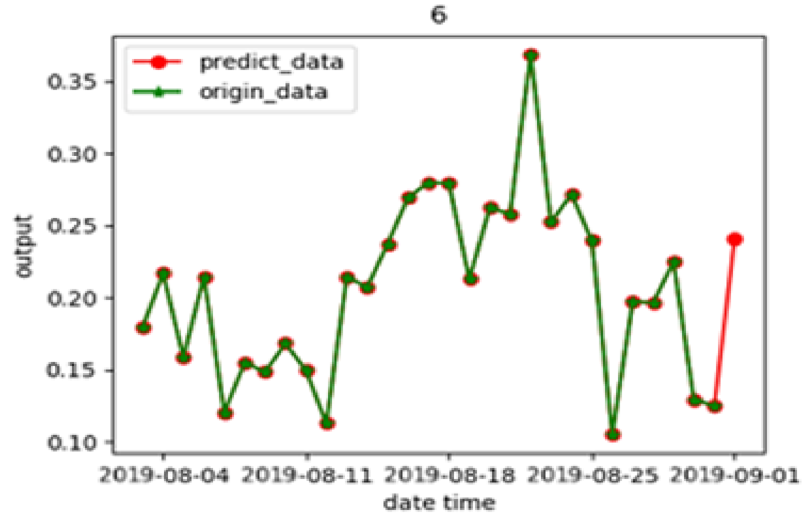
$$min(max)\, Z = F(k_1, k_2, \dots, k_n), \tag{4}$$

$$s.t. \begin{cases} \sum_{i=1}^{n} \quad k_i = 1, \\ (k_i \geq 0, i = 1,2,\dots,n), \end{cases}$$

The objective function can be considered as some kind of error index or precision index, and is expressed as $F(k_1, k_2, \dots, k_n)$, $k_1, k_2, \dots, k_n$, is the N-heavy weight coefficient of the non-negative single forecasting model. After multiple verification, different models are given different weights. The comparison between the predicted value obtained by weighted calculation and the original value is shown in Fig 3.



(a)



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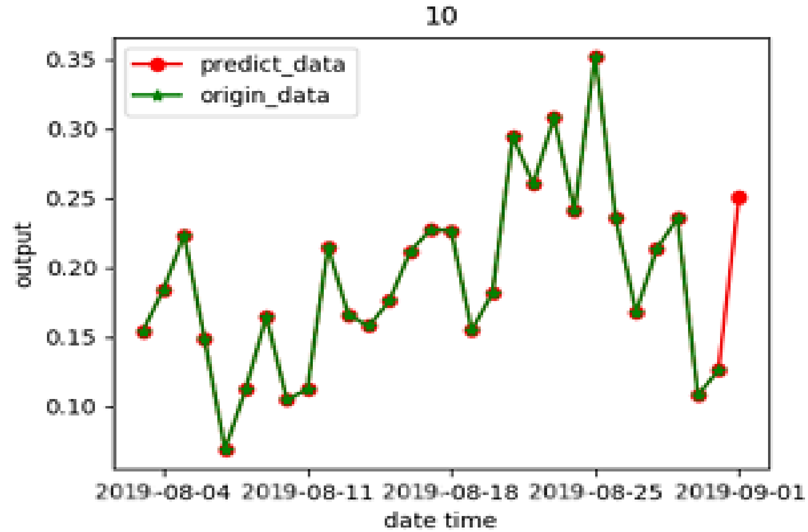

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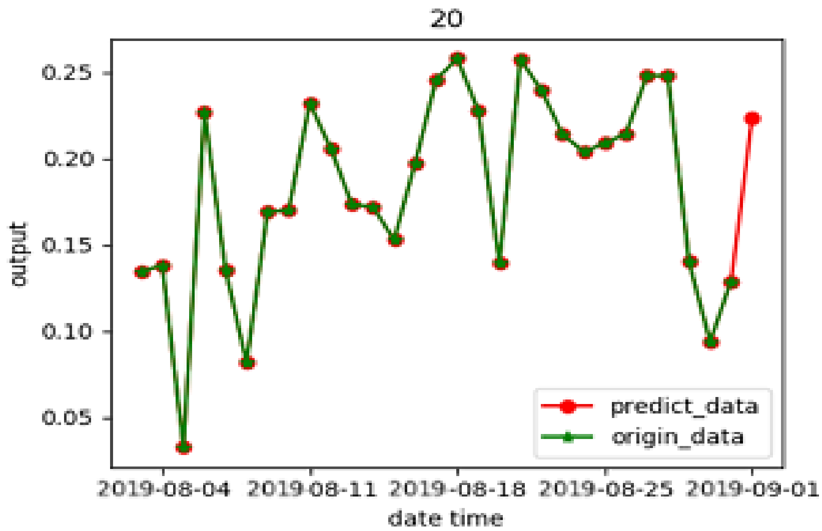

(d)

Fig 3 Comparison of prediction results of the combined algorithm (hourly mean graph of 0, 6, 10, and 20 points)

D. Model Validation

The combined model composing three basic time series prediction algorithms (exponential smoothing algorithm, GM grey prediction algorithm, phase space algorithm), which are frequently used at present, is validated to observe its effect. To facilitate the subsequent calculation of Mean Absolute Deviation and Root Mean Squared Error (RMSE), the original and predicted gas values at the same time were selected.

The results of original value selection and the predicted value at 0 are shown in Table 2.

Table 2. Comparison table of gas prediction results at 0

Date	Gas original value at 0	The predicted value of gas at 0
2019.08.03	0.145416667	0.139430556
2019.08.04	0.163041667	0.171930556
2019.08.05	0.183541667	0.184944444
2019.08.06	0.179958333	0.175680556
2019.08.07	0.178875	0.175694444
2019.08.08	0.187666667	0.186388889
2019.08.09	0.214	0.215305556
…	……	……
2019.08.21	0.203916667	0.197930556
2019.08.22	0.163875	0.173013889
2019.08.23	0.150583333	0.155013889
2019.08.24	0.115708333	0.116305556
2019.08.25	0.131333333	0.130291667
2019.08.26	0.179291667	0.176069444
2019.08.27	0.117083333	0.1105
2019.08.28	0.160083333	0.165180556
2019.08.29	0.098583333	0.097180556
2019.08.30	0.112291667	0.11175
2019.08.31	0.12925	0.124736111

The Mean Absolute Error (MAE) can be calculated as follows:

$$MAE(x,h) = \frac{1}{m}\sum_{i=1}^{m} |h(x_i) - y_i| \tag{5}$$

Root Mean square Error (RMSE) can be calculated as follows:

$$\text{RMSE}=\sqrt{\frac{1}{m}\sum_{i=1}^{m} (y_i - \hat{y}_i)^2} \tag{6}$$

By selecting the true value and the predicted value at the same time to calculate the prediction error, the prediction results of the combined model are better than those of the single model, whether judged by the combined model MAE or the RMSE. MAE and RMSE reach 0.007% and 0.009% respectively, and the accuracy can reach 98.21%. It shows that the combined model is better than the single prediction results of the three time series prediction methods, and meets the expected standard. It can accurately predict the gas emission amount, which is very important for practices.

4. Conclusions and Future Works

The prediction of the gas emission law of coal mining face is realized to predict the gas data trend, use the data to measure and use the root mean square error and average absolute error indicators to measure the accuracy of the gas emission prediction results, verify that the prediction accuracy rate can reach 98.21%.

Modern system theory to predict production safety in coal mine safety production is in the process of application. The accuracy and accuracy of the state model of coal mine safety production in the forecasting process will be further improved. Under the strict requirements of coal mining safety regulations, the state model of coal mine safety production will develop towards the direction of more in line with the requirements of safety assessment. Thus, the safe mining of coal mine will have a more solid and reliable theoretical basis and more accurate and advanced technical support. Further research is needed in the following aspects:

On the premise of guaranteeing the information circulation, how can a full coal mine safety production state model be applied in the process of the actual mine mining in a more complete and efficient manner. In the application process, what emergency measures can be taken to improve the stability of the model to a greater extent and thus improve the safety coefficient of the mining process and ensure the safety of life and property of enterprises and employees.

Table 3. Comparison table of prediction error values

	MAE（%）	RMSE（%）
Exponential smoothing method	0.012	0.019
GM	0.019	0.023
Phase space reconstruction method	0.009	0.008
Combined forecasting method	0.007	0.009

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