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Application of Artificial Intelligence Algorithms in Coal Mine Methane Monitoring and Prediction

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Abstract The introduction of advanced data processing and prediction models can effectively improve the accuracy and timeliness of coal mine safety supervision and reduce safety hazards. In this paper, an artificial intelligence-based coal mine gas monitoring and prediction method is proposed, and an improved LSTM-TimeGAN model is constructed by processing and analyzing the gas monitoring data. The method firstly utilizes the LSTM model to predict the environmental factors such as temperature and humidity, and then generates the gas data through the improved TimeGAN model and combines it with the LSTM to predict the gas concentration. The experimental results show that the prediction accuracy using this model is significantly better than the traditional method. Specifically, the prediction results using the improved LSTM-TimeGAN model are 0.01163, 0.06265, and 0.00476 in MSE, RMSE, and MAE metrics, respectively, which are significantly lower than those of the traditional TimeGAN and LSTM-TimeGAN models. The model not only captures the time dependence of gas concentration, but also effectively improves the stability of data generation. With this method, more accurate early warning of gas concentration can be provided in actual coal mine production to effectively improve safety.

Index Terms Coal mine safety, gas monitoring, artificial intelligence, LSTM, TimeGAN, data processing

I. Introduction

Coal is the main energy source in China, and with the increase in the depth and intensity of coal mining, gas accidents occur from time to time. However, the utilization and mining of coal are facing great challenges and threats, and coal mine gas accidents have always been an important factor threatening the safe production of mines, and the prevention and control of gas disasters is a major need for the safe and efficient production of coal mines [1], [2]. At present, as the mining depth of the mine increases, the gas content also rises, and once a gas accident occurs in a coal mine, it is bound to cause considerable casualties [3]. Therefore, in order to prevent and reduce the occurrence of coal mine gas accidents, it is necessary to strengthen the monitoring and management of coal mine gas and take effective safety measures to ensure the safety and stability of coal mine production [4]-[6].

With the progress of science and technology, coal mine gas management technology has been continuously innovated and optimized. Among them, artificial intelligence technology, especially machine learning algorithm, plays a key role in gas monitoring [7]. Machine learning algorithms mine the laws and patterns of data by learning from a large amount of data, which in turn improves the accuracy and timeliness of prediction [8], [9]. Machine learning-based models can analyze gas concentration data in real time, identify abnormal fluctuations, and predict future concentration changes [10], [11]. This not only helps in early warning of gas leakage risk, but also helps in gas control optimization for intelligent gas management [12]. In addition, AI technology can adapt to the changes in the coal mine environment through continuous learning and optimization, with good adaptive ability and reliability, which further improves the efficiency and effectiveness of gas monitoring [13]-[15]. Based on this, promoting the construction of an artificial intelligence-based coal mine gas monitoring and prediction system can effectively reduce the risk of gas discharge and improve the efficiency of resource utilization, thus maximizing the economic and environmental benefits [16]-[18].

This paper proposes an improved model based on the combination of LSTM and TimeGAN. TimeGAN, as a generative adversarial network (GAN) model, is capable of generating time-series data that approximates the true distribution, and it is particularly suitable for the generation and prediction of multidimensional time-series data. By combining LSTM with TimeGAN, the model is able to improve the prediction accuracy of coal mine gas concentration while generating data, and further improve the robustness of prediction. The innovation of this study is that through the improved LSTM-TimeGAN model, the coal mine gas data is modeled in multiple dimensions, and the missing values and outliers in the data are handled, while the effective generation and prediction of complex time series data is achieved. This provides a new technical path for coal mine safety management and can provide strong data support and technical guarantee for gas concentration monitoring and early warning system.

II. Artificial Intelligence Based Coal Mine Gas Monitoring and Prediction Model Construction

II. A. Data acquisition

In the process of data acquisition, the sensors and acquisition system can monitor the changes in the environment inside and outside the mine in real time, providing high-frequency dynamic data, which are transmitted to the central processing system for subsequent analysis. Data processing technology mainly includes data preprocessing, data cleaning, data fusion and feature extraction. By removing noise, filling in missing values and detecting anomalies in the collected raw data, the quality and integrity of the data are ensured. Subsequently, data from different types of sensors are integrated through data fusion technology, and multi-sensor data fusion algorithms are utilized to improve the accuracy and reliability of the data. In the feature extraction stage, combining statistical analysis and machine learning algorithms, key features are extracted from massive data to provide input for model training and risk prediction. Through these advanced data acquisition and processing technologies, the coal mine safety monitoring system is able to realize comprehensive, accurate and real-time monitoring of the mine environment. The data collected and processed through the data acquisition and processing technologies monitor and process the data from a variety of coal mine environmental parameters, which includes data cleaning, fusion and feature extraction steps, to provide reliable data support for the safety early warning system.

II. B. Data processing

Since the gas data is affected by various factors such as migration action and noise, the data is characterized by nonlinearity and instability, and considering the effect of different factors such as noise on the nonlinear data, the data thus obtained cannot be directly used in the prediction of the gas outflow. Thus, it is necessary to perform pre-processing operations on the data to further determine the optimal parameters to be used in the prediction module to ensure the accuracy of the model.

II. B. 1) Coal mine monitoring data analysis

Underground mine monitoring system can use different types of sensors based on a certain range of sampling period, real-time monitoring of underground environmental parameters including: temperature, gas concentration, oxygen concentration and wind speed, etc., and then through the underground transmission network to the monitoring center of the resulting monitoring values, and then generated a time series, the formation of the time series can be through different angles and levels of the working face of different time periods to reflect the environmental information. The formed time series can reflect the environmental information of the working face in different time periods through different angles and levels.

Depending on the number of observed variables in the resulting time series, they can be categorized into unitary time series (UTS) and multivariate time series [19] (MTS). In this paper, we study arrays of time series belonging to multivariate time series.

(1) Data reliability analysis

Whether the data collected through the coal mine safety monitoring system is reliable directly affects the construction of gas prediction model, such as if the underground sensor is not calibrated according to the requirements, then it will inevitably lead to a large error, resulting in the monitoring of the data does not have a good reliability, at this time, it is required to be in the field of the relevant calibration technicians by improving the professional competence and level of the data to make it more reliable.

(2) Part of the data is missing

Generally speaking, the underground monitoring system observes the cycle of fixed checking time to complete the real-time monitoring data collection and transmission, however, due to the complexity of the overall environment of the mine underground, which is affected by a variety of factors, so the sensor equipment, data transmission network and power supply system often fails, which will inevitably lead to the loss of part of the monitoring data.

(3) Data abnormality

Because of the poor working environment of underground production, there are often many different interference factors, and they will produce a certain degree of influence in the signal output process of the sensor equipment, which will lead to the existence of abnormal data.

II. B. 2) Missing value processing

Missing values are handled as follows:

(1) Determine whether there are missing value data

Determine the missing value is generally used isnull (), generated by all the data of the true / false matrix, the corresponding position of all the elements are listed, the element is empty or NA on the display of True, otherwise it is False.

(2) Filtering missing data

Objects with missing information attribute values are removed to get a complete information table. This will use the dropna () function, based on the value of the label there is no data among the missing data to complete the axis label data filtering, you can adjust the tolerance of missing values through the threshold.

(3) Fill/replace missing data

In the case of more data can be filtered out directly, while less missing data, data filling is necessary. fillna () function, with the specified value or interpolation method to fill the missing values.

(4) Interpolation of missing values

Usually, the interpolation methods used include multiple interpolation and regression interpolation. Among them, the regression interpolation method means that the prediction of missing values is realized by using a regression model. Multiple interpolation is the process of generating a complete set of data within a relevant data set with missing values and constructing the complete data set, and then operating like this many times to form a random sample of missing values.

II. B. 3) Handling of outliers

In this paper, we utilize the mean correction method to complete the processing of anomalous data, assuming that in a certain interval of time length T, the monitoring data at the moment of t $\left(t = T / N, n \in N^*\right)$ is x_t, and if there is an anomaly in the monitoring data of $t_i\left(i = 1, 2, \cdots, n\right)$ at a certain moment of time during the period, the anomalous monitoring data in the sequence can be replaced with the mean value :

$$x_{t_i} = \frac{\sum_{t=t_{i-1}}^{t_{i-1}} x_t + \sum_{t=t_{i+1}}^{n} x_t}{n-1} \tag{1}$$

where, x_{t_i} - monitoring data at t_i moment, $(n-1)$ - the number of monitoring data in T time interval.

II. B. 4) Data normalization

Using Zscore normalization for this process is a relatively simple process of dividing the difference between the mean of one sample and the mean of the reorganized sample ground by the standard deviation of the reorganized sample. To wit:

$$z = (x - \mu) / \sigma \tag{2}$$

where, x - that sample, μ - the mean of that group of samples, σ - the standard deviation of the group of samples.

The amount of Z -value represents the distance between the mean of the original sample and the mean of the reorganized group of samples, calculated in units of standard deviation. When this sample is below the mean of the group of samples Z is negative, and vice versa.

II. B. 5) Data set partitioning

Before functionalized modeling, we first divide the data by dividing the sample dataset into two parts: the training set and the test set. Among them, the training set is used to train the model samples; while the test set is the sample set left alone during the model training process, which is mainly used for the model's ability evaluation. In this paper, we use eighty percent of the data as the training set and twenty percent of the data as the test set after randomly sorting all the data.

II. C.Theory of correlation analysis

In data analysis, correlations are often used to mine data for hidden relationships and draw constructive conclusions. Typical examples in coal mine safety posture include coal accident correlation analysis, which finds that the number of coal mine accidents is much higher than other days in hot weather by modeling and analyzing weather and accidents. In correlation analysis, the study of nonlinear correlation is also one of the hotspots, and the kernel function can effectively evaluate the nonlinear relationship, which is categorized into multi-accounting method for sparse data, multi-step accounting, integrated multi-accounting, clustered multi-accounting, and high-efficiency multi-accounting.

In addition, unitary variable analysis and multivariate variable analysis are two major types in association typing, the former mainly focuses on the correlation between unitary variables, and the methods to measure its correlation are cross-entropy, covariance, and KL dispersion, while the latter mainly focuses on the correlation between multivariate variables, and the methods to measure its correlation are typical correlation analysis, principal component analysis, and cluster analysis. In this paper, the theory of correlation analysis is used to describe the correlation information between gas sensors in the field of coal mine safety posture, and thus used in gas missing value filling.

Cross entropy plays a great role in correlation analysis and is also often used as a loss function in deep learning, the formula for cross entropy is as follows:

$$H(X,Y)=\sum_{i}X(i)\log\left(\frac{1}{Y(i)}\right) \tag{3}$$

where $X(i)$, $Y(i)$ represent the probability of variable X for i, the probability of variable Y for i, and $H(X,Y)$ represents the cross-entropy between variables X and Y, respectively.

KL scatter simulates the distribution of data, also known as relative entropy, which should obey the principles of non-negativity, asymmetry, etc., and the formula for KL scatter is as follows:

$$KL(X\parallel Y)=\sum_{i}X(i)\log\left(\frac{X(i)}{Y(i)}\right) \tag{4}$$

$$KL(Y\parallel X)=\sum_{i}Y(i)\log\left(\frac{Y(i)}{X(i)}\right) \tag{5}$$

where $KL(X\parallel Y)$ represents the forward scatter and $KL(Y\parallel X)$ represents the backward scatter.

The covariance is often used to measure the correlation between elements. The closer the correlation coefficient is to 1, the stronger the positive correlation between the two elements, and conversely, the closer the correlation coefficient is to minus 1, the stronger the negative correlation between the two elements, and the formula for covariance is as follows:

$$\begin{aligned}Cov(X,Y)&=E\left[(X-E(X))(Y-E(Y))\right]\\&=E(XY)-2E(X)E(Y)+E(X)E(Y)\\&=E(XY)-E(X)E(Y)\end{aligned} \tag{6}$$

where $E(X)$ and $E(Y)$ are the expectations of X and Y, respectively, and $\mathrm{Cov}(X,Y)$ represents the covariance.

When the elements are numerically very different, the Pearson correlation coefficient can be used to shield the magnitude from the problem, calculated as follows:

$$\rho_{XY}=\frac{Cov(X,Y)}{\sqrt{D(X)}\sqrt{D(Y)}} \tag{7}$$

where $D(X)$ and $D(Y)$ represent the variance of X and Y, respectively, and ρ_{XY} represents the Pearson correlation coefficient.

II. D.Improving the LSTM -TimeGAN model

II. D. 1) LSTM model

LSTM is an improved version of RNN model [20], which is mainly used to solve the problem of gradient vanishing and gradient explosion that exists in the training process of RNN model, and through the three gating units of input gate, oblivion gate and output gate, it can effectively consider the dependence relationship between the historical long term information and the current information, and improve the prediction accuracy, and the main internal computational process is as follows:

$$f_t=\sigma\left(W_f\cdot[h_{t-1},x_t]+b_f\right) \tag{8}$$

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right) \tag{9}$$

$$o_t = \sigma\left(W_o \cdot [h_{t-1}, x_t] + b_o\right) \tag{10}$$

$$c_t = f_t \circ c_{t-1} + i_t \circ \tilde{c}_t \tag{11}$$

$$h_t = o_t \circ \tanh(c_t) \tag{12}$$

where f_t is the output of the forgetting gate; σ is the sigmoid function; W_f, W_i, W_o are the weight matrices of the forgetting gate, the input gate, and the output gate, respectively; h_{t-1}, h_t are the outputs of the cell cell cell of the previous moment, the output of the cell cell at the current moment; x_t is the input of the cell cell at the current moment; b_f, b_i, b_o are the bias terms of the forgetting gate, the input gate, and the output gate, respectively; c_{t-1}, c_t are the state of the cell at the previous moment, and at the current moment, respectively; i_t is the output of the forgetting gate; $\tilde{c}_t$ is the output of the candidate memory cell unit; o_t is the output of the output gate; and $\tanh$ is the hyperbolic tangent function.

II. D. 2) TimeGAN model

TimeGAN model [21] effectively solves the problem of generating and autoregressing data augmentation models in time series in coal mine gas monitoring by combining unsupervised and supervised learning. TimeGAN model divides the features of the time series data into two categories, static and dynamic features, which are represented as the vectors S, X, the corresponding vector space is ζ, χ, respectively, the main purpose is to obtain the potential feature distribution $\hat{p}(S, X_{1:T})$ by using real data for training, so that it is similar to the static feature vector and dynamic feature vector distribution $p(S, X_{1:T})$ as similar as possible.

The main structure of TimeGAN consists of two parts: the self-coding module and the adversarial network, where the self-coding module contains the embedding function and the recovery function, and the embedding function is to convert the static and dynamic features into hidden features; the adversarial module contains the generator and the discriminator, and the generator obtains the hidden features consisting of the static and dynamic features through the generating function, while the discriminator carries out the classification of the hidden features, returning its probability of being real data and generated data.

The TimeGAN model uses three kinds of loss functions in the training process, firstly, the optimization of the self-encoder encoding and decoding process is carried out by using the out-of-context reconstruction loss L_R to obtain efficient low-dimensional hidden features; secondly, the generator's ability to learn the real data features and potential features is evaluated by the supervised loss L_S between the real data and the generator; finally, the unsupervised loss L_U based on the antagonistic module achieves the generator's Feedback. The three loss functions are:

$$L_R = E_{S,X_{1:T}\sim p}\left[\left\|S - \tilde{S}\right\|_2 + \sum_t \left\|X_t - \tilde{X}_t\right\|_2\right] \tag{13}$$

$$L_S = E_{S,X_{1:T}\sim p}\left[\left\|h_t - g_\chi(h_s, h_{t-1}, z_t)\right\|_2\right] \tag{14}$$

$$\begin{aligned} L_U = {} & E_{S,X_{1:T}\sim p}\left[\log y_s + \sum_t \log y_t\right] \\ & + E_{S,X_{1:T}\sim \hat{p}}\left[\log(1-\hat{y}_s) + \sum_t \log(1-\hat{y}_t)\right] \end{aligned} \tag{15}$$

II. D. 3) Forecasting process

Firstly, the measured temperature, humidity and coal dust data were preprocessed and divided into training and testing sets. When LSTM is used for temperature prediction, the measured temperature and humidity data are used as inputs and the measured coal dust data are used as outputs in the training period, the parameters of the LSTM model are determined after training, and the measured temperature and humidity data in the testing period are inputted into the trained model, so as to obtain the coal dust prediction results of the LSTM model in the testing period and carry out the accuracy evaluation.

When the improved Time GAN-LSTM is used for temperature prediction, the measured temperature data, temperature and humidity data of the training period are firstly inputted into the Time GAN model, and the generated temperature data and its corresponding temperature and humidity data are obtained based on the Time GAN model, and the quality of the generated data is analyzed by comparing the generated data with the measured data; and then the measured and generated temperature and humidity data are used as the Then, the measured and generated temperature and humidity data are used as inputs, and the corresponding measured and generated coal dust data are used as outputs to train the LSTM model; finally, the measured coal dust and rainfall during the test period are inputted into the trained model to obtain the coal dust prediction results of the improved Time GAN-LSTM model during the test period, and then the accuracy is evaluated.

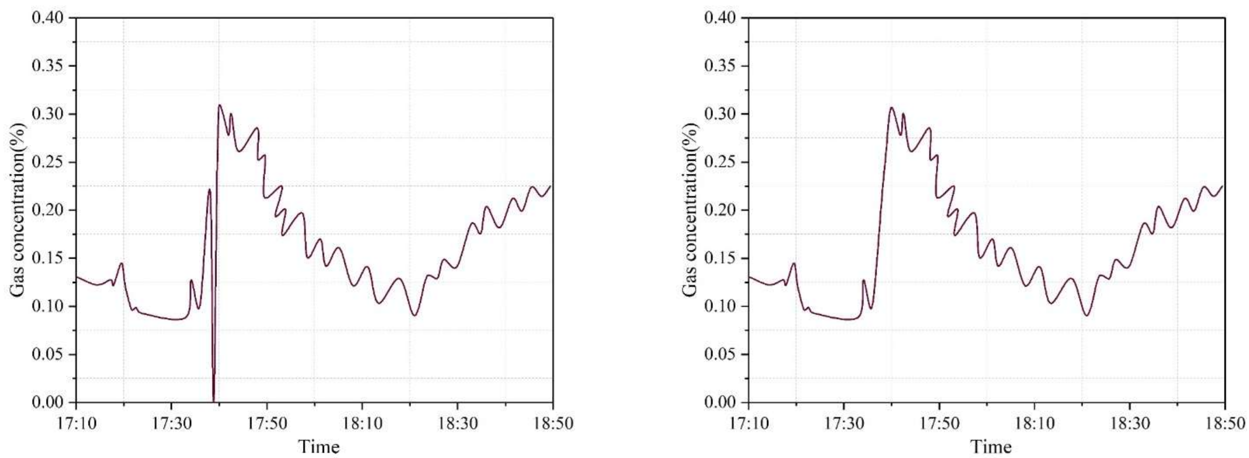
III. Analysis of the effect of application in coal mine gas monitoring and prediction modeling

III. A. Analysis of the effect of data set preprocessing

III. A. 1) Missing values and outliers treatment effects

(1) Missing values

In this paper, given data points are used to construct an interpolating polynomial through these points to interpolate predictions between data points. The Lagrange polynomial is utilized to process the missing values in the gas monitoring data series. Examples of the dataset before and after the processing of missing values are shown in Fig. 1, where (a) and (b) represent the data performance before and after correction, respectively. The results show that the missing values disappear after the method out of this paper and the corrected results are more in line with the real situation.

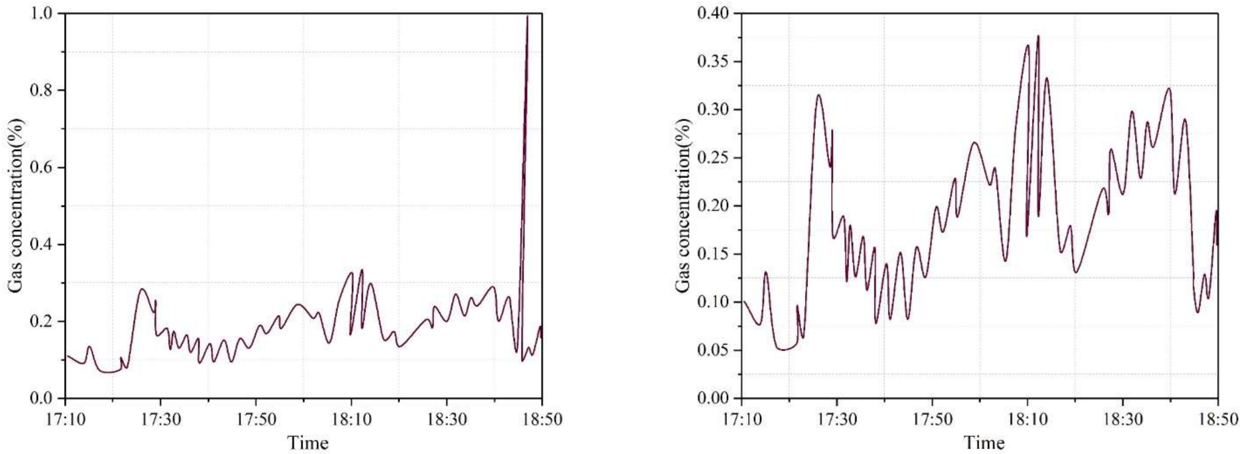


(a)Preprocess (b)After process

Figure 1: Examples of data set deletion value processing

(2) Outliers

Coal mine monitoring data can be abnormal due to malfunction or damage of the sensor itself, improper human operation or intentional interference with the monitoring equipment, inaccurate or untimely calibration of the equipment, and other reasons. Abnormal data will reduce the accuracy of model prediction, so it is necessary to deal with them. In this paper, we choose to consider the anomalies as missing values and then adopt the use of statistical methods to predict or correct the anomalies. This method preserves the sample size and does not directly discard the outliers, which can more accurately reflect the actual situation of the data. Examples of the data set before and after correction of outliers are shown in Fig. 2, where (a) and (b) represent the data performance before and after correction, respectively. Obviously, the regularity of the corrected data is more obvious and the predicted results are closer to the real values.



(a)Preprocess (b)After process

Figure 2: Examples of data set anomaly value modification

III. A. 2) Parametric analysis of gas concentration in the working face

In the process of production, the working face gas concentration is associated with a variety of factors. In this paper, the following three major factors are chosen as reference:

(1) Inlet airflow, upper corner and return airflow gas concentration

In the U-shaped ventilation system, the airflow paths of the inlet and return airflow are fixed. The concentration of gas in the inlet air stream is directly related to the quality of the air entering the working face. If the gas concentration in the inlet air stream is high, the air entering the working face will also contain a higher concentration of gas. The gas concentration in the return-air alley will also have an impact on the gas concentration in the working face.

(2) Ventilation system

The ventilation system of the mining area has an important relationship with the gas concentration and the distribution of gas in the working face, and proper regulation and control of the ventilation system is one of the important means to ensure that the gas concentration in the working face is stabilized at a safe level. When the wind speed increases, due to the increase of negative pressure and air leakage in the mining area, the power of the wind flow is enhanced, and it can penetrate more deeply into all corners of the mining area. This results in the high concentration of gas in the extraction zone being difficult to be brought out effectively, while the gas near the working face may accumulate due to the reduced wind speed. As a result, the concentration of gas in the wind flow will gradually increase in the case of reduced wind speed.

(3) Environmental factors

Environmental factors are mainly reflected in the two aspects of gas outflow and temperature. When the amount of gas outflow increases, if the ventilation conditions of the working face remain unchanged, the gas concentration in the airflow will increase accordingly. This is because an increase in the amount of gas outflow means that more gas gas enters the working face, and the ventilation system cannot take this gas away in a timely and effective manner, which leads to an increase in the concentration of gas in the airflow. An increase in temperature increases the diffusion rate of gas molecules in the coal seam or in the air, which accelerates the movement and diffusion of the gas in the coal seam, and makes it easier for the gas to be released into the ventilation system of the mine.

III. A. 3) Validation analysis of gas concentration correlation coefficients in the working face

In order to select appropriate covariates when building the prediction model, quantitative analysis is used to identify monitoring data with strong correlation with gas concentration, and statistical methods are used to measure the degree of correlation between different monitoring data and gas concentration levels. In this paper, Pearson correlation analysis is chosen to quantitatively analyze and visualize the correlation coefficients, and the correlation coefficients are screened to improve the accuracy of the prediction model. The reference dataset of correlation coefficients of gas concentration in the working face is shown in Table 1. The results show that the results of four tests for each parameter indicate that the difference between the test results of each parameter is very small after using the model of this paper, which proves that the performance of the method of this paper is very stable and the following experiments can be carried out.

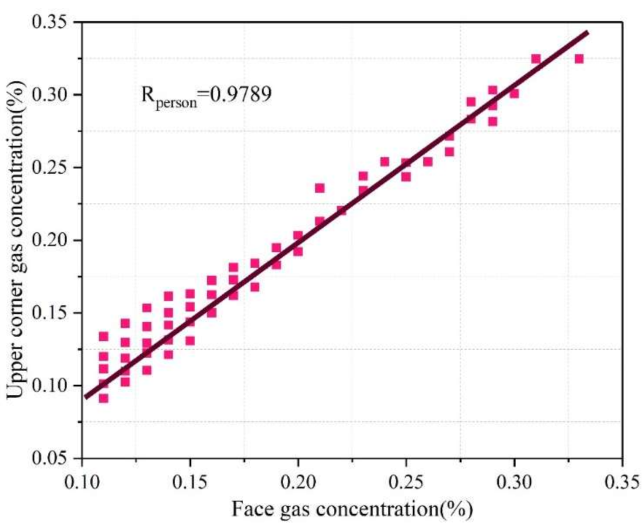
Table 1: Reference data set of the contact parameter of the working face

Parameter name	Test frequency			
	1	2	3	4
Face gas concentration(%)	0.1662	0.1687	0.1684	0.1682
Return air gas concentration(%)	0.1592	0.1583	0.1593	0.1606
Inlet air gas concentration(%)	0.1011	0.1003	0.0985	0.1005
Upper corner gas concentration(%)	0.1726	0.1705	0.172	0.1715
Wind speed(m/s)	1.2695	1.2686	1.271	1.2674
Temperature (℃)	14.2237	14.7073	14.8001	14.4276
Dust concentration(mg/m^3)	2.2998	2.2978	2.3009	2.3013
Gas flow(m^3/min)	1.4998	1.5015	1.4987	1.5017

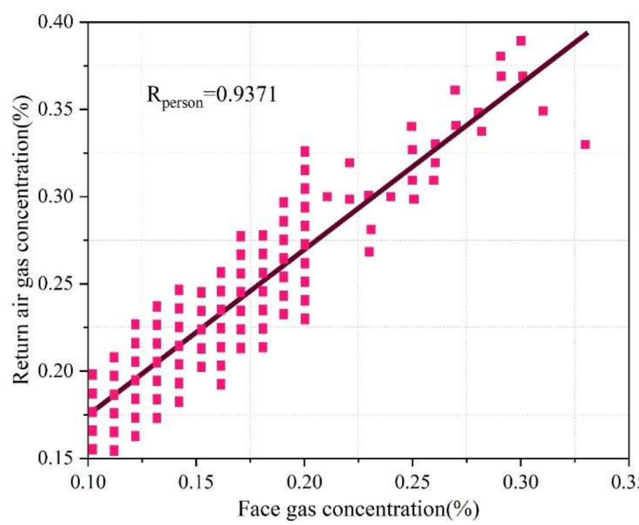
The reference data set of gas concentration correlation coefficients used in this paper is validated and analyzed, and the Pearson coefficient is calculated. The Pearson's correlation coefficients between the gas concentration at the working face and each correlation coefficient are shown in Table 2, and the correlation between the gas concentration at the working face and each correlation coefficient is shown in Fig. 3, in which (a) to (c) represent the gas concentration at the upper corner, the gas concentration in the return airflow and the gas outflow, respectively. According to Pearson's correlation coefficient, it can be seen that there is a certain correlation between the gas concentration in the working face and each correlation parameter, and the correlation is stronger with the gas concentration in the return airflow, the gas concentration in the upper corner and the gas outflow, and there is a correlation with the gas concentration in the inlet airflow, temperature, wind speed and coal dust concentration, but the correlation is weak, so the strong correlation parameter is chosen to be the input parameter of the model.

Table 2: Pearson correlation coefficient of gas concentration and parameter

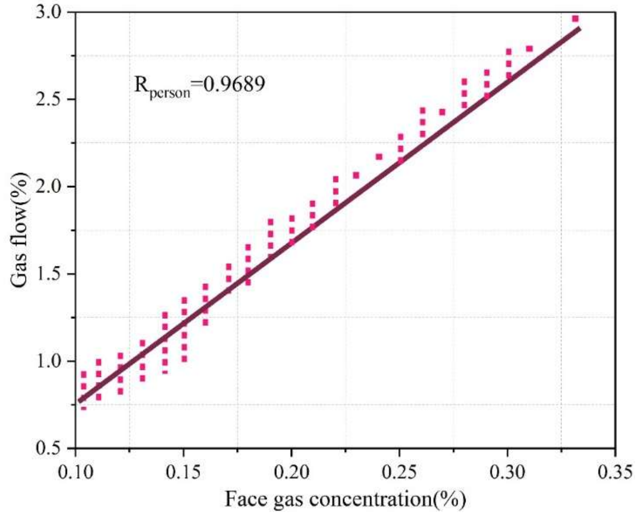
Parameter name	Pearson correlation coefficient
Face gas concentration	1.0000
Inlet air gas concentration	0.4724
Return air gas concentration	0.9371
Upper corner gas concentration	0.9789
Wind speed	0.5883
Dust concentration	0.491
Gas flow	0.9689
Temperature	0.2902



(a)Upper corner gas concentration



(b)Return air gas concentration



(c)Gas flow

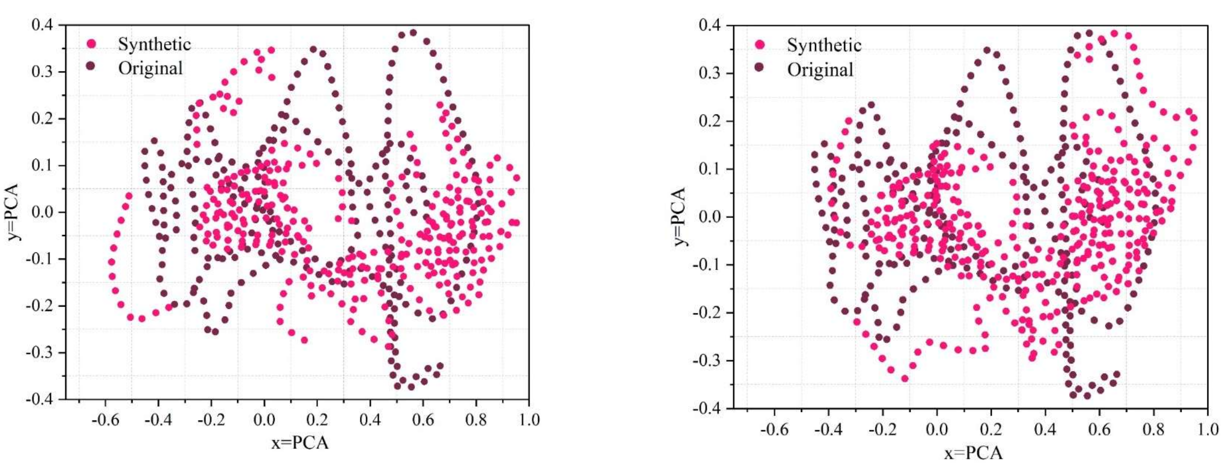
Figure 3: The concentration of the face gas and the parameters of the work

III. B. Analysis of the predictive effect of coal mine gas monitoring

The validity of the proposed coal mine gas prediction model is verified next. When generating data, the generative models used for comparison include: traditional TimeGAN network, LSTM-TimeGAN network and the algorithm proposed in this paper called Improved LSTM-TimeGAN network. In gas prediction, the data generated by different generative models are used as a training set and the existing data set is used as a test set to compare the prediction results. In which the prediction model is unified using LSTM, network parameters: number of neurons in LSTM unit: 60, number of LSTM layers: 3, batch size: 34, number of iterations: 350, optimizer: Adam, loss function: MSE, activation function: RELU.

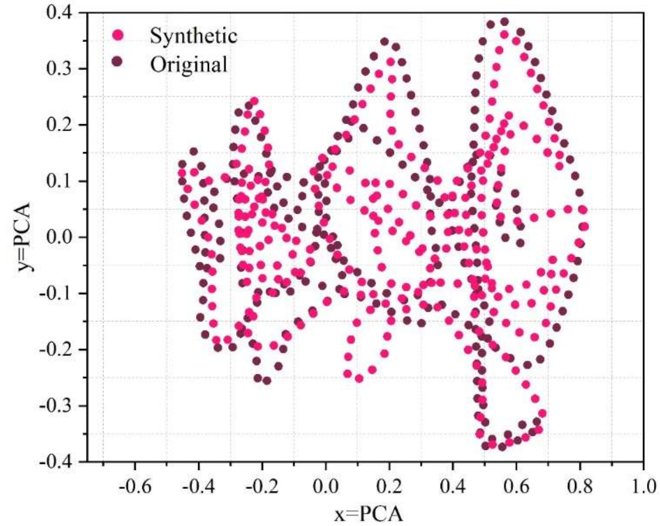
III. B. 1) Results of network generated data distribution under different models

Figure 4 shows the results of the PCA-based network generated data distribution for different models, where (a) ~ (c) represent TimeGAN network, LSTM-TimeGAN network and Improved LSTM-TimeGAN network, respectively. It can be seen that compared to TimeGAN and LSTM-TimeGAN generation models, the improved TCN-TimeGAN network is more capable of capturing the temporal dependence of the data during the training process, and it is not only capable of generating the centralized portion of the data, but also takes into account the other data distribution points, which ensures the data diversity, so that the generated data can cover and track the real data distribution, and the generated data higher quality.



(a) TimeGAN

(b) LSTM-TimeGAN

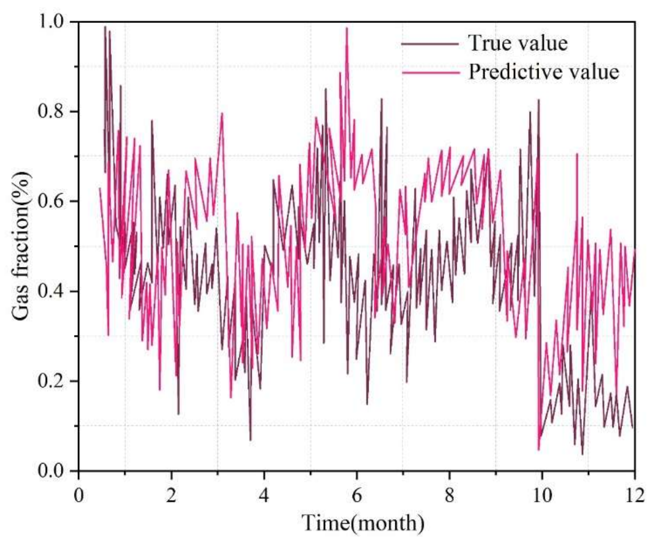


(c) Improved LSTM-TimeGAN

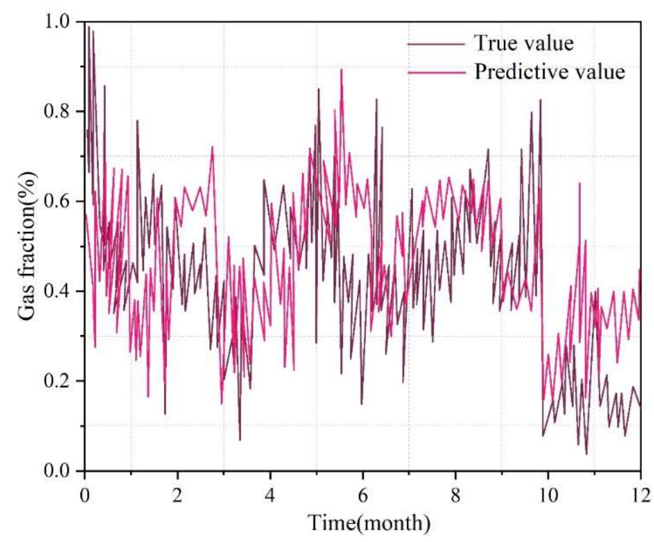
Figure 4: Different models generate data distribution based on PCA networks

III. B. 2) Prediction results of different models

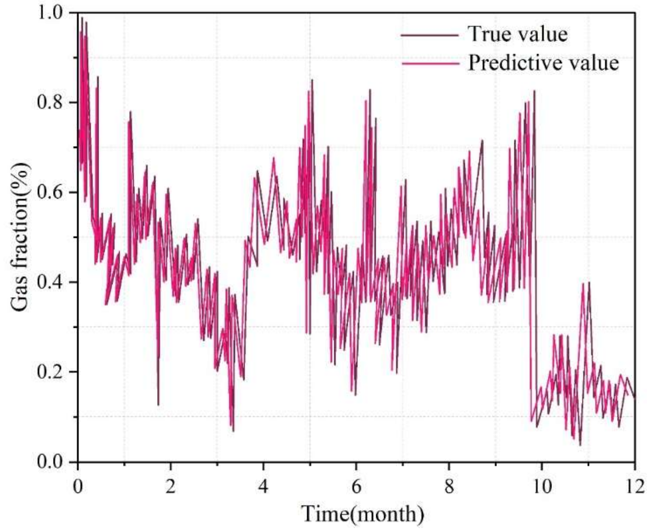
Figure 5 shows the prediction results of different models, where (a) ~ (c) represent TimeGAN network, LSTM-TimeGAN network and Improved LSTM-TimeGAN network, respectively. The prediction results of the data generated by different models are shown in Table 3. It can be seen that the data generated by the comparison models are able to maintain a more stable and accurate prediction in the early stage, but as the training process proceeds, all the comparison models except the proposed model have different degrees of deviation and are unable to maintain a stable prediction in all time periods, which fully proves the effectiveness of the data generated by the model in predicting the gas. From the quantitative index values of the data generated by different models for gas prediction, it can be seen that the MSE, RMSE and MAE values obtained from the prediction using the data generated by the model proposed in this paper are much smaller than those of the comparison models. It is clear that the improved TCN-TimeGAN method proposed in this paper improves the difficulties faced by the traditional loss function, such as asymmetry and gradient vanishing; and further improves the training stability and prediction quality by adding a gradient penalty term with adaptive weights to the discriminative network loss function.



(a) TimeGAN



(b) LSTM-TimeGAN



(c) Improved LSTM-TimeGAN

Figure 5: Prediction of different models

Table 3: Prediction results of data generated by different models

Model	MSE	RMSE	MAE
TimeGAN	0.03755	0.19667	0.10552
LSTM-TimeGAN	0.05951	0.24524	0.15717
Improved LSTM-TimeGAN	0.01163	0.06265	0.00476

IV. Conclusion

The study shows that the improved LSTM-TimeGAN model demonstrates obvious advantages over traditional methods in coal mine gas monitoring and prediction. By predicting environmental factors such as temperature, humidity, coal dust, etc., and combining the data generated by TimeGAN, the model in this paper can significantly improve the accuracy of gas concentration prediction. The experimental results show that the improved LSTM-TimeGAN model outperforms the traditional model in several evaluation metrics, especially in the MSE, RMSE and MAE metrics, which reach 0.01163, 0.06265 and 0.00476, respectively. These results show that the stability and accuracy of gas concentration prediction can be effectively improved by using the improved model.

In addition, the prediction results of the different models used in the experiments on the generated data also show that the improved LSTM-TimeGAN model achieves a significant improvement in both the stability of data generation and the prediction accuracy of gas concentration. With this model, more accurate gas concentration prediction can be realized in the process of coal mine production, so as to improve the timeliness and accuracy of mine safety warning and reduce the risk of safety accidents caused by gas leakage.

In summary, the improved LSTM-TimeGAN model provides an innovative and efficient technical means for coal mine gas prediction, which can significantly improve the prediction ability of the coal mine safety monitoring system and provide powerful technical support for mine safety management.

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References

[1] Fu, G., Xie, X., Jia, Q., Tong, W., & Ge, Y. (2020). Accidents analysis and prevention of coal and gas outburst: Understanding human errors in accidents. Process safety and environmental protection, 134, 1-23.

[2] Miao, D., Lv, Y., Yu, K., Liu, L., & Jiang, J. (2023). Research on coal mine hidden danger analysis and risk early warning technology based on data mining in China. Process Safety and Environmental Protection, 171, 1-17.

[3] Deokar, S. R., & Wakode, J. S. (2017). Coal mine safety monitoring and alerting system. International Research Journal of Engineering and Technology, 4(3), 2146-2149.

[4] Li, H., Zhang, Y., & Yang, W. (2023). Gas explosion early warning method in coal mines by intelligent mining system and multivariate data analysis. PLoS one, 18(11), e0293814.

[5] Jo, B. W., & Khan, R. M. A. (2017). An event reporting and early-warning safety system based on the internet of things for underground coal mines: A case study. Applied Sciences, 7(9), 925.

[6] Ma, J., & Dai, H. (2017). A methodology to construct warning index system for coal mine safety based on collaborative management. Safety Science, 93, 86-95.

[7] Shi, W., Li, J., Chen, Z., Zhang, C., & Yang, H. (2024, December). Smart Mine: The Role of Artificial Intelligence in Modern Coal Extraction. In 2024 IEEE/WIC International Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT) (pp. 874-879). IEEE.

[8] Chen, P., Xie, Y., Jin, P., & Zhang, D. (2018). A wireless sensor data-based coal mine gas monitoring algorithm with least squares support vector machines optimized by swarm intelligence techniques. International Journal of Distributed Sensor Networks, 14(5), 1550147718777440.

[9] Bi, S., Shao, L., Qi, Z., Wang, Y., & Lai, W. (2023). Prediction of coal mine gas emission based on hybrid machine learning model. Earth Science Informatics, 16(1), 501-513.

[10] Doğan, H. E., & Demirel, N. (2025). Analyzing lump coal gas release as a source of coal mine methane: Using GC and machine learning. Fuel, 397, 135433.

[11] Sharma, M., & Maity, T. (2024). Review on machine learning-based underground coal mines gas hazard identification and estimation techniques. Archives of Computational Methods in Engineering, 31(1), 371-388.

[12] Wen, H., Yan, L., Jin, Y., Wang, Z., Guo, J., & Deng, J. (2023). Coalbed methane concentration prediction and early-warning in fully mechanized mining face based on deep learning. Energy, 264, 126208.

[13] You, M., Li, S., Li, D., & Xu, S. (2021). Applications of artificial intelligence for coal mine gas risk assessment. Safety science, 143, 105420.

[14] Sikora, M., & Sikora, B. (2006). Application of machine learning for prediction a methane concentration in a coal-mine. Archives of Mining Sciences, 51(4), 475-492.

[15] Vallejo-Molina, L., Blandon-Montes, A., Lopez, S., Molina-Escobar, J., Ortiz, A., Soto, D., ... & Molina, A. (2024). Application of artificial intelligence to the alert of explosions in Colombian underground mines. Mining, Metallurgy & Exploration, 41(4), 2129-2142.

[16] Tutak, M., Krenicky, T., Pirník, R., Brodny, J., & Grebski, W. W. (2024). Predicting methane concentrations in underground coal mining using a multi-layer perceptron neural network based on mine gas monitoring data. Sustainability, 16(19), 8388.

[17] Demirkan, D. C., Duzgun, S., Juganda, A., Brune, J., & Bogin, G. (2022). Evaluation of time series artificial intelligence models for real-time/near-real-time methane prediction in coal mines. CIM Journal, 13(3), 97-106.

[18] Bai, Q. (2025). Application of Artificial Intelligence Technology in Coal Mine Mechanical and Electrical Equipment. Journal of Artificial Intelligence and Information, 2, 57-62.

[19] Gang Tan,Yueyang Wang,Ziyi Xiao,Dandan He & Guodong Sa. (2025). From a multi-period perspective: A periodic dynamics forecasting network for multivariate time series forecasting. Pattern Recognition,167,111760-111760.

[20] Xiao Wang. (2025). Application of multimodal fusion in automatic image classification: Combining CNN and RNN model. Intelligent Decision Technologies,19(2),928-942.

[21] Peihao Tang,Zhen Li,Xuanlin Wang,Xueping Liu & Peng Mou. (2025). Time Series Data Augmentation for Energy Consumption Data Based on Improved TimeGAN. Sensors,25(2),493-493.