Research on prediction of rockburst microseismic parameters based on CNN-LSTM hybrid model

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Abstract. Time series prediction of parameters is a method of learning existing observational data and predicting its future evolution, which has been applied in many fields. In this paper, the key microseismic indexes are mined to describe the rockburst development, and a hybrid prediction model of CNN-LSTM neural network combining convolutional neural network (CNN) and long-short-term memory neural network (LSTM) is proposed. This model uses the good feature extraction capabilities of CNN and the special memory prediction function of LSTM neural network to achieve accurate prediction of microseismic indexes. The model can avoid the problem of determining index weights and is completely driven by data. It effectively combines qualitative and quantitative analysis to reduce the impact of human factors. The model is tested with the microseismic monitoring data of the E-han Expressway Grand Canyon Tunnel. The results show that when predicting cumulative energy, cumulative apparent volume, and energy index, the root mean square error (RMSE) of the CNN-LSTM hybrid model is reduced by 9.5%, 7.2%, and 8.3%, respectively, compared with the single LSTM neural network model. The model can effectively provide a scientific basis for the prediction of rockburst microseismic parameters in similar projects.

1. Introduction

With the increase of in-situ stress level of deep engineering, rock burst disaster of underground engineering is more and more prominent, which has caused extremely serious impact on production safety. The so-called rock burst refers to the sudden release of elastic potential energy accumulated in deep rock mass under excavation or external disturbance, resulting in the phenomenon of peeling and ejection of surrounding rock mass[1], which is a sudden dynamic instability geological disaster. As a bottleneck problem in transportation and mining projects, such disasters have become a hot research issue in the fields of large-scale deep engineering and mineral resources exploitation[2].

A large number of scholars at home and abroad have constructed different rockburst criteria or prediction criteria from a specific factor or perspective. For example, Ma Tianhui et al[3] proposed the rockburst early warning criterion of Jinping II Hydropower Station in accordance with the obvious regularity of the distribution of rockburst in time, space and intensity. Tang Chunan et al[4], Xu Nuwen et al[5-6], Ma Ke et al[7] successfully applied the microseismic monitoring system to Zhangmatun Iron
Mine, Dongjiahe Coal Mine, underground water-sealed petroleum tunnel and other projects, and carried out early warning research on rock burst and surrounding rock stability caused by rock mass instability and failure. The rapid development of computer technology accelerates the research and application of artificial intelligence methods in various industries, including rock burst disaster prediction. For example, Shang Yuequan et al. proposed a prediction model based on the combination of particle swarm optimization algorithm and generalized regression neural network based on the existing rock burst data. Zheng Yuchao et al. selected evaluation factors according to engineering practice and established a prediction model of rockburst based on the grey correlation BP neural network based on entropy weight. Tang Zhili et al. built a prediction model of rockburst based on nine kinds of machine learning algorithms by comprehensively considering several rock burst influencing factors.

Above, many methods about rock burst forecast warning from different angles, has achieved fruitful research results, but because of the complexity of the rock burst inoculation mechanism, there are still worthy of further research aspects: rock burst is by the qualitative and fuzzy factors mutual influence, through mathematical mechanics analysis method is difficult to achieve full accurately analyze; The rockburst early warning method based on microseismic monitoring technology does not fully consider the influence of time factor and cannot predict the state and danger degree of surrounding rock in a certain period in the future. Based on the excellent feature extraction ability of convolutional neural network (CNN) and the unique memory prediction function of long and short memory neural network (LSTM), an improved hybrid prediction model of CNN-LSTM neural network is proposed in this paper. The model can avoid the problem of determining the index weight, and is completely driven by data, which reduces the influence of human subjective factors. The model is applied to the prediction of microseismic parameters of the E-han Expressway Grand Canyon tunnel. The results show that, when the cumulative energy, cumulative apparent volume and energy index are predicted, Compared with the single LSTM neural network model, the root mean square error (RMSE) of the CNN-LSTM hybrid model decreases by 9.5%, 7.2% and 8.6%, respectively, and the MAPE accuracy increases by 11%, 15.3% and 12.7%, respectively. The model can effectively provide a scientific basis for the prediction of rock burst microseismic parameters in similar projects.

2. Theoretical basis and model construction

2.1. Long-short time memory network
As a kind of cyclic neural network (RNN), LSTM is superior to other kinds of neural network models in processing sequence data due to its chain network structure. The key to LSTM is the control of long-term state $C$, which changes information to the state of the cell through the gate structure, as shown in figure 1.

![Figure 1. LSTM cell structure diagram](image)

In the LSTM unit, the first interaction structure is the forgetting gate, which is used to select and retain information in the past state $C_{t-1}$ and the current state $C_t$. Its expression is as follows:
\[ f_t = \sigma(W_f \cdot [s_{t-1}, x_t] + b_f) \]  

The second interaction structure is the input gate. The input gate controls the transmission of sequence information to the current cell state \( C \) and processes the sequence information of the current input. The input gate has two modules. The first module is used to determine the update status of information, and the second module uses the \( \tanh \) function to determine the candidate information for update at the current moment.

\[ i_t = \sigma(W_i \cdot [s_{t-1}, x_t] + b_i) \]
\[ \tilde{c} = \tanh(W_c \cdot [s_{t-1}, x_t] + b_c) \]  

The third interaction structure is the computing structure of the current moment unit state \( C_t \), which determines the increase and deletion of information through the decision of forgetting gate and input gate.

\[ C_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \]  

The final interaction structure is the output gate. The \( \tanh \) function determines the output of the current cell state. The output decision is multiplied by the output information to get the information that needs to be output at this moment.

\[ o_t = \sigma(W_o \cdot [s_{t-1}, x_t] + b_o) \]
\[ s_t = o_t \odot \tanh(C_t) \]  

In the formula, \( W_f, W_i, W_c, W_o \) represent matrix weights of each gate respectively, \( b_f, b_i, b_c, b_o \) represents the offset items of each gate respectively; \( \odot \) means that the elements are multiplied bit by bit, \( f_t, i_t, \tilde{c}_t, C_t, o_t, s_t \) are the state of forget gate, input gate, input node, state unit, output gate and intermediate output respectively.

2.2. **CNN-LSTM time series prediction model**

Convolutional Neural Networks (CNN), originally developed for reading two-dimensional image data, can also be applied to the prediction of one-dimensional time series. The CNN model is placed at the front end of LSTM, which can effectively extract and learn the features of one-dimensional time series data, learn the sub-sequences to be input, and convert these sub-sequences into shapes that can be interpreted by LSTM model. This hybrid model is called CNN-LSTM. The hybrid model of CNN-LSTM neural network is mainly composed of two parts: the main function of CNN module is to extract and integrate the features of the input data; The LSTM neural network module is to memorize and screen the integrated features, make fitting prediction, and finally output the prediction results. The structure of CNN-LSTM is shown in Figure 2.

![CNN-LSTM structure diagram](image)

Figure 2. CNN-LSTM structure diagram

In order to make the predicted values of each microseismic parameter more in line with the actual situation of field monitoring, the predicted results need to be optimized. The one-dimensional timing series data is divided into input/output samples, and 12 step sizes are taken as input and 1 step size is taken as output. Each sample is divided into 2 subsamples, and each subsample has 6 time steps. CNN
can provide time series interpretation of each subsequence of the LSTM model for processing as input, and re-use the same CNN model to read each subsequence of data. The CNN model is first used to read the convolutional layer of the subsequence, followed by the maximum pooled layer, and then flattens the structure into a single one-dimensional vector to be used as a single input time step of the LSTM layer. The LSTM part of the prediction model was defined, and the activation function was set as "Sigmoid". Adam algorithm and MSE loss function were used to optimize it. This part explained the CNN model's reading of the input sequence and made predictions.

3. Case analysis

3.1. Brief description of engineering geological conditions
The E-han Expressway Grand Canyon Tunnel is a super-long double-track tunnel, with its entrance end located in Wendian Village, Jinkouhe District, and its exit end in Eerkutan Village, Ganluo County, Liangshan Prefecture. The total length is about 12.1km. As the "world's first buried highway tunnel" at present, its buried depth is up to 1,940m. Under the influence of actual geological conditions, the Grand Canyon tunnel has a great chance to face disasters such as collapse, rock burst and water inrush. Since the construction of the tunnel, according to the feedback of the site staff, March 11, 2020, At 04: 30 PM, the right line pile number K77+060 of Grand Canyon Tunnel (Emei) occurred rockburst at 2.5m above the designed baseline of the left side wall in the process of risk removal, resulting in rock ejection phenomenon and accompanied by clear sound. After the ejection rock mass was broken down, one on-site duty personnel suffered leg fracture. According to the field investigation results, the intensity of the rock burst was medium, and there were several weak-medium rock bursts in the follow-up. Rockburst disaster poses a great threat to the personnel and equipment in the process of tunnel construction and affects the construction progress. At the same time, a large amount of energy release caused by high ground stress leads to the fracture and loosening of surrounding rock. The broken surrounding rock will directly affect the initial support and indirectly affect the secondary lining, resulting in certain risks in the use and operation stage of the tunnel.

3.2. Experimental data processing and model construction
The data source of this experiment is a total of 744 sets of microseismic monitoring data on the right line of the E-han Expressway Grand Canyon Tunnel. The microseismic energy, apparent volume and its cumulative value and energy index are selected to construct the database. Due to the different magnitudes of indicators such as accumulated energy, accumulated apparent volume, and energy index. In order to solve the problems of slow calculation speed and poor model accuracy caused by large differences in data magnitudes, it is necessary to standardize the data before model training. The calculation formula is as follows:

\[ \bar{X} = \log_{10} X / 10 \]  
\[ \bar{X} = \frac{X - \min(X)}{\max(X) - \min(X)} \]

Among them, X is the microseismic parameter used, and \( \bar{X} \) represents the processed value.

In model training, it is very important to select the appropriate time window (time step). When the time window is too large or too small, it is difficult for the model to fully extract the effective features of the time series of microseismic parameters, thus affecting the prediction performance of the model. After repeated trial calculations, the input length of the time window was set to 12, so the input sample dimension of the LSTM timing series prediction model was 12×1. Table 1 shows the structure and parameter Settings of the prediction model.

| Table 1. Model structure and parameter settings |
|-----------------------------------------------|
| Model Component | Output | Kernel/Stride | Activation Function |
| CNN 1 | 12×64 | 2/1 | Elu |
CNN 2 12×128 2/1 Elu
Pool 1 6×128 2/2
Flaten 128
LSTM 1 6×256 2/1 Elu
Flaten 256
Dense 1 64 Sigmoid
Dense 2 1 Sigmoid

MAE, RMSE and MAPE were selected as the indexes to evaluate the prediction effect of the model. MAE focused on the prediction error in the stationary state. The smaller MAE was, the better the prediction effect was. RMSE focuses on the prediction error of peak time. Similarly, the smaller RMSE was, the better the prediction effect was. MAPE measures the average value of absolute percentage error sum of each point, which describes the overall prediction effect, and is also the main basis for evaluating the prediction effect of the model in this study. The calculation formulas of MAE, RMSE and MAPE are as follows:

\[
MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \bar{y}_i| \tag{9}
\]

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \bar{y}_i)^2} \tag{10}
\]

\[
MAPE = \sum_{i=1}^{n} \left| \frac{y_i - \bar{y}_i}{y_i} \right| \times 100 \frac{n}{n} \tag{11}
\]

In the formula, \(y_i\) and \(\bar{y}_i\) are the observed value and predicted value, respectively, and \(n\) is the data sample size.

3.3. Analysis of prediction results

(a) Accumulated energy  
(b) Cumulative apparent volume  
(c) Energy index
4. Conclusion

In this paper, a hybrid prediction model of CNN-LSTM neural network combining convolutional neural network (CNN) and long and short term memory neural network (LSTM) is proposed. The model can make full use of the excellent feature extraction ability of convolutional neural network (CNN) and the unique memory prediction function of LSTM network. The model was applied to the prediction of microseismic parameters in the E-han Expressway Grand Canyon tunnel. The results show that the prediction trend of each parameter is accurate and the accuracy is higher, and the accuracy is better than the traditional LSTM prediction model. Traditional prediction method of rock burst is focused on the potential level of rock burst prediction, and with the aid of microseismic monitoring method, to calculate the sequential predict seismic parameters, combined with the future trend of the evolution of microtremor index (for example, in the process of rockburst with microseismic events increased, cumulative depending on the volume of the sudden increase, a sudden decrease of energy index), can better explain the risk of rock burst, with the characteristics of timberliness, to provide more response time for engineering response. The construction of these models is helpful to reveal the evolution trend of the key characteristics of rock burst development in the future and provide effective technical means for the prediction and early warning of rock burst disaster in deep underground engineering.

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