INTRODUCTION

Rock bursts are a common dynamic disaster in coal mines, and they crucially affect the safety, economics, and efficiency of mining operations. The mitigation and control of rock bursts is challenging owing to their violent, unpredictable characteristics.1,2 Rock bursts are characterized by the sudden release of elastic strain energy in rock and coal during mining or roadway excavation. The mining-induced redistributed high-stress regions around surrounding rocks are crucial for the evaluation of rock bursts risk, particularly when using the longwall mining method. The excavation is surrounded by thick layers of hard, intact rock capable of storing high levels of strain energy.3 Therefore, the determination of mining-induced stresses is essential for the evaluation of rock bursts risk in coal mines. Several approaches have been employed to assess and calculate the stress distribution around the extraction field, such as empirical and analytical,4–9 numerical simulation,10–15 and field monitoring16–20 approaches.

Prediction of longwall mining-induced stress in roof rock using LSTM neural network and transfer learning method

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Abstract
Real-time monitoring of three-dimensional stress in the field is an effective approach to detect evolving stress in roof rock and to evaluate rock bursts risk. However, the sensors or data transmission cables may be damaged due to the volatile environment found in coal mines, which can lead to the loss of relevant monitoring data, and some critical information for rock burst prediction may be missed entirely. A number of methods that use historical data to predict missing data or future structural states have been proposed. However, the performance of these methods is poor when the training data are insufficient owing to lack of data. To address this issue, a methodology framework is proposed to predict the mining-induced stress when some monitoring data are missing. The framework uses a long short-term memory neural network integrated with the transfer learning method. The proposed method can transfer the knowledge learned from complete monitored data of adjacent sensor to target sensor to boost forecasting. A case study has been conducted to evaluate the method. The results show that the developed model can significantly improve the prediction performance for the target domain, which can be improved further by increasing the size of the target domain training data available.

KEYWORDS
data missing, LSTM, mining-induced stress, monitoring, stress prediction, transfer learning

1 | INTRODUCTION

Rock bursts are a common dynamic disaster in coal mines, and they crucially affect the safety, economics, and efficiency of mining operations. The mitigation and control of rock bursts is challenging owing to their violent, unpredictable characteristics.1,2 Rock bursts are characterized by the sudden release of elastic strain energy in rock and coal during mining or roadway excavation. The mining-induced redistributed high-stress regions around surrounding rocks are crucial for the evaluation of rock bursts risk, particularly when using the longwall mining method. The excavation is surrounded by thick layers of hard, intact rock capable of storing high levels of strain energy.3 Therefore, the determination of mining-induced stresses is essential for the evaluation of rock bursts risk in coal mines. Several approaches have been employed to assess and calculate the stress distribution around the extraction field, such as empirical and analytical,4–9 numerical simulation,10–15 and field monitoring16–20 approaches.
Three-dimensional (3D) stress monitoring is a crucial and effective approach for revealing the stress state, predicting rock burst events, and adopting countermeasures in coal mines. Generally, long-term stress monitoring is helpful for analyzing and predicting the evolution of stresses in surrounding rock. Therefore, the accuracy and reliability of early disaster warnings rely on the quantity and quality of the in situ monitoring data. However, the sensors and data transmission cables are often damaged in the volatile environment in underground mines, which leads to the loss of monitoring data. The loss of data greatly affects the early warning of surrounding rock instability. Therefore, it is essential to reconstruct the missing data and predict the stress state in the following few days to enable evaluations of safety, reliability analyses, and real-time early warnings of disasters. The reconstruction and completion of missing data in field monitoring can be converted to a time series prediction task, and the process has been studied widely. Numerous methods of model-based and data-driven approaches have been proposed in the structure health monitoring (SHM) field. These approaches include time series state space modeling, autoregressive modeling, Gaussian process modeling, Bayesian multi-task learning methodologies, support vector regression methodologies, and long short-term memory (LSTM) neural networks. However, the performance of these methods is highly dependent on the quantity of training data available. When monitoring data are lost due to the failure of sensors or optical fiber cables, sufficient training data may not be available to train the models. Conventional methods do not perform well with insufficient data. Therefore, in this situation, how to improve the prediction accuracy is a critical issue.

To this end, an LSTM neural network based on transfer learning for stress prediction is proposed. The LSTM neural network is a special and advanced recurrent neural network (RNN) that is capable of learning the long and short time series patterns from historical data. This type of networks has been proved to exhibit excellent performance for addressing time series problems and has the best performance compared with the other algorithms. Recently, LSTM neural networks have been wildly used and achieved great success in civil engineering, for example, stress-strain behavior of soils, tunneling-induced ground settlement, performance of EPB shield tunneling, and seismic bearing capacity of foundations. However, few studies have been performed to predict the mining-induced stress using LSTM neural networks. More importantly, insufficient training data limit the effective performance of such a network. Therefore, in this study, we integrate the LSTM neural network and the transfer learning method to predict the mining-induced stress and improve the prediction accuracy. Transfer learning, on the other hand, is an important development in machine learning that aims to improve the prediction performance by transferring knowledge learned from source domains to target domains. The source domain refers to the domain with knowledge and more labeled data and is the object that is to be transferred. The target domain refers to a new but related domain with a small amount of labeled data and is the object to which the knowledge is transferred. To test and verify the proposed method, we selected the vertical stress data of monitored results in a coal mine as a case study. The results show that the developed model can significantly improve the prediction performance for the target domain, which can be improved further by increasing the size of the target domain training data available.

This paper is organized as follows. Section 2 presents a detailed analysis of a field case study of a stress monitoring scheme and the results of the study. The methodology framework of the proposed model, base theory of the LSTM network, and transfer learning are described in Section 3. In Section 4, a case study of a model application and experiments over two datasets of adjacent monitoring sections are described, and corresponding experimental results and analysis are presented. Section 5 concludes the paper.

2 | BACKGROUND: IN SITU REAL-TIME STRESS MONITORING IN COAL MINE

2.1 | Geological and mining conditions at Dongtan coal mine

The Dongtan coal mine is located in Ji-ning, Shandong, China (Figure 1). The longwall panel in this study was the 6303 working face. One side of the 6304 panel had been previously extracted. The protective coal pillar between the 6303 panel and the gob was 5-m-wide. The panel overburden depth was approximately 660 m, and the panel was 245-m-wide and 1400-m-long. The immediate roof of the panel comprised mudstone and had an average thickness of 0.8 m. The main roof was fine-grained sandstone with an average thickness of 12.9 m. The immediate floor of the panel was composed of siltstone and was approximately 1.54-m-thick. The main floor comprised fine-grained siltstone and was approximately 7.7-m-thick. The detailed information geological conditions of panel 6303 are shown in Figure 1. As shown in Figure 1, the geological conditions of the monitoring sections from S-1 to S-6 are relatively simple, and they are not located in densely faulted areas. To avoid the influence of geological conditions on
this study, we selected the monitoring section of S-3 and S-4 as the research subject.

2.2 Monitoring scheme

The working face of the 6303 panel experienced frequent microseismic events during extraction, which were closely related to the high-stress distribution around the mining area. A Fiber Bragg Grating (FBG) borehole deformation sensor for stress measurement in coal mine roof rock is adopted. The details of the measurement technique can be found in the literature. To ensure accurate monitoring of the long-term stress changes during the mining process, sensors were installed in the intact homogenous main roof. This installation avoided the difficulties associated with drilling and installing sensors in the soft coal.

According to the theory of rock mechanics, stress in rock involves both in situ stresses $\sigma_{ij}^0$ and excavation-induced stresses $\Delta\sigma_{ij}$. The in situ stresses in a rock mass depend largely on the geological structure, such as discontinuities, faults, folds, and dikes. Excavation-induced stresses are due to the mining process or nearby activities such as excavation, blasting, or pumping. Therefore, the real stress state of the rock mass is the sum of in situ stresses and induced stresses, which can be denoted as follows.

$$\sigma_{ij} = \sigma_{ij}^0 + \Delta\sigma_{ij}$$

Therefore, the monitoring of the dynamic evolution of mining-induced stress should include two steps, the investigation of the in situ stresses and real-time investigation of the induced stresses.

First, we measured the in situ stresses using the overcoring stress measurement method for the 6303 working face before long-term monitoring. The in situ stresses measured by overcoring tests are shown in Table 1. As shown in Figures 2 and 3, eight FBG borehole stress sensors were installed in the main roof of the 6303 panel at different section positions ahead of the working face. The sensor installation inclination was approximately 35°, the depth was approximately 15–20 m, and the distance between adjacent sensors was approximately 90 m. The detailed information of these stress monitoring boreholes is shown in Table 2. Figure 4 shows the core with sensor by overcoring test and on-site installation work. The dynamic 3D stress was obtained by the sensors with the variations of strains that were calculated from the variation of

| TABLE 1 | The in situ stresses |
|----------|---------------------|
| **Geodetic coordinate system** | **Working sector coordinate system** |
| Principal stress | Value (MPa) | Azimuth angle (°) | Oblique angle (°) | Stress components | Value (MPa) | Stress components | Value (MPa) |
| $\sigma_{11}$ | 33.2 | 167.20 | 4.36 | $\sigma_{xx}$ | 16.96 | $\tau_{xy}$ | −0.52 |
| $\sigma_{22}$ | 24.2 | 68.51 | 63.23 | $\sigma_{yy}$ | 33.09 | $\tau_{yz}$ | −0.64 |
| $\sigma_{33}$ | 15.2 | 259.37 | 26.36 | $\sigma_{zz}$ | 22.43 | $\tau_{cx}$ | −3.61 |
wave lengths and the results of three normal stresses and three principal stresses within the rock mass. To illustrate the stress evolution law and data characteristics, normal stress measurements were taken from only two sections (S-2 and S-3) for a detailed analysis.

2.3 Variation of normal stresses

The magnitude and distribution of existing in situ stresses around a coal seam are disturbed by a goaf formed due to underground mine excavation. Figure 5 shows typical monitoring results of the changes in the three normal stresses \( \sigma_{xx}, \sigma_{yy}, \sigma_{zz} \) in the monitoring sections S-2 and S-3. The three normal stresses vary, as shown in Figures 5(a) and 3(b). The figures show that the stress states in the monitoring sections are not affected by mining disturbance and are similar to the in situ stresses at distances >80 m from the working face. As the working face advances the three normal stresses increase; the vertical stress increases rapidly compared to the other two horizontal stresses. At a distance of about 20 m ahead of the working face, all the three normal stresses reach a peak and then decrease sharply because the integrity of the roof and coal seam is violated.

To quantitatively evaluate the degree of disturbance to the roof rock mass caused by mining activities, we assume that \( k_1, k_2, \) and \( k_3 \) are the corresponding stress concentration coefficients of the ratio of the three normal stresses to in situ stresses. The values of the coefficients when the working face is at different distances from the monitoring section can be calculated using the following equation:

\[
\begin{align*}
\sigma_{xx} &= k_1 \sigma_{xx}^0 \\
\sigma_{yy} &= k_2 \sigma_{yy}^0 \\
\sigma_{zz} &= k_3 \sigma_{zz}^0 
\end{align*}
\]

Figure 6 shows the variations of the concentration coefficients of the three normal stresses during the coal mining
process. Therefore, the area ahead of the working face can be divided into four zones, namely, the in situ stresses zone, slightly disturbed zone, violently disturbed zone, and stress relief zone according to the values of the coefficients.

From above, field measurement can more directly reflect the distribution and variation law of mining-induced stress, and the monitoring data are essential for rock burst warning and prevention. However, it is ubiquitous and inevitable that monitoring data may be lost due to sensor malfunction, optical fiber cable damage caused by coal mining activities, and the volatile environment. Because of lost data, information that is critical for safety evaluation may not be available. Thus, data that can be recovered when the sensor fails or short-term stress data predictions can have important implications for the diagnosis and prognosis of disasters in coal mines. For example, relevant destress measures can be adopted to mitigate high-stress concentration, and an early warning can be raised timely. Therefore, in the next section, a methodology framework of an LSTM neural network that integrates transfer learning is proposed for stress prediction.

### 3 | METHODOLOGY FRAMEWORK

Figure 7 shows a flowchart of the methodology proposed in this study, and the algorithm of ensemble of the LSTM and transfer learning method is shown in Table 3. To summarize, the ensemble of LSTM and transfer learning method can be generalized into the following steps. First, the time series datasets $D_S = \{ (x^S_1, t^S_1), (x^S_2, t^S_2), \ldots, (x^S_n, t^S_n) \}$ and $D_T = \{ (x^T_1, t^T_1), (x^T_2, t^T_2), \ldots, (x^T_n, t^T_n) \}$ are collected to serve as source domain and target domain, respectively. Second, time series dataset $D_S$ is preprocessed by rolling window method to obtain time series samples. The LSTM neural network is used to predict the stress; thus, the next step is to construct a base LSTM model using the source domain data. The grid search method is used to optimize the hyperparameters for the base model. Subsequently, the parameter transfer approach is used to complete knowledge transfer. The weights of hidden layers and the hyperparameters of the above pre-trained base LSTM model act as initialization parameters of the target LSTM model over the target domain data. The model parameters are then fine-tuned according to the test results. The proposed model is used to improve the prediction accuracy to overcome the missing data problem resulting from sensor or optical fiber cable damage caused by mining activities.

#### 3.1 | LSTM neural network

Long short-term memory is a special RNN that is applicable to time series problems, compared to RNNs or
traditional neural networks, which is best able to solve vanishing gradient and exploding gradient problems of long time series. A single LSTM cell comprises an input gate, a forget gate, an output gate, and the cell state memory (Figure 8). Gates are used to optionally perform information saving, adding, or deleting using the activation functions, thereby updating the cell state to achieve long-term storage of information and resolve the dependence of the time series on time. More specifically, the input gate controls the flow of input activation into the internal cell state. The forget gate controls the LSTM cell to forget or reset the cell’s memory adaptively. The output gate controls the flow of output activation into the LSTM cell output.\textsuperscript{31} The activation functions are \textit{sigmoid} and \textit{tanh}.

\begin{equation}
\text{sigmoid}(x) = \frac{1}{1 + e^{-x}}
\end{equation}

\begin{equation}
\text{tanh}(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}
\end{equation}

\textbf{Algorithm 1 The Algorithm of Ensemble of the LSTM and Transfer Learning}

\textbf{Input:} Source domain time series dataset $$D_{S} = \{(x_{1}^{S}, t_{1}^{S}), (x_{2}^{S}, t_{2}^{S}), ..., (x_{N}^{S}, t_{N}^{S})\}$$

- Target domain time series dataset $$D_{T} = \{(x_{1}^{T}, t_{1}^{T}), (x_{2}^{T}, t_{2}^{T}), ..., (x_{N}^{T}, t_{N}^{T})\}$$
- Rolling window size $$\Delta t$$
- Learning rate $$\eta$$
- Hidden layer $$L$$
- Hidden units $$U$$
- Epoch times $$I$$
- Forecast horizon $$h$$

\textbf{Output:} The final model generated by the ensemble LSTM and transfer learning.

\textbf{Pretreatment:} Time series dataset $$D_{S}$$ is preprocessed by rolling window method to obtain time series samples.

\begin{equation}
\text{For } D_{S} = \{(x_{1}^{S}, t_{1}^{S}), (x_{2}^{S}, t_{2}^{S}), ..., (x_{N}^{S}, t_{N}^{S})\}
\end{equation}

Calculate the autocorrelation coefficients $$\rho_{\Delta t}$$ according to Eq. (16).

Determine the $$\Delta t$$ according to the values of $$\rho_{\Delta t}$$.

The $$D_{S}$$ was divided into $$K = N - (\Delta t + h) + 1$$ time series samples.

1. \textbf{For } $$D_{S} = \{(x_{1}^{S}, t_{1}^{S}), (x_{2}^{S}, t_{2}^{S}), ..., (x_{N}^{S}, t_{N}^{S})\}$$

\begin{enumerate}
\item Build a base LSTM model, set $$h = 1$$, and set a group appropriate values for each parameters of $$\eta$$, $$L$$, $$U$$, and $$I$$.
\item Traverse the parameter combination to optimize the LSTM model by grid search method.
\item Calculate the RMSE according to Eq. (13).
\item Get an optimal pre-trained LSTM model.
\end{enumerate}

2. \textbf{For } $$D_{T} = \{(x_{1}^{T}, t_{1}^{T}), (x_{2}^{T}, t_{2}^{T}), ..., (x_{N}^{T}, t_{N}^{T})\}$$

\begin{enumerate}
\item Build a new LSTM model, set $$h=1$$, $$\Delta t_2=\Delta t_1$$.
\item Transfer the weights of hidden layers and hyperparameters of $$h = 1$$, $$\Delta t$$, $$\eta$$, $$L$$, $$U$$, and $$I$$ from the above optimal pre-trained LSTM model act as initialization parameters of the new LSTM model over the $$D_{T}$$.
\item Fine-tune the new model according to Eq. (13–15).
\end{enumerate}

\textbf{End For}

At the time phase $$t$$ ($$t = 1, ..., n$$) and inside the $$l$$th LSTM network layer, the input state of the LSTM cell is $$x_{l}^{(i)}$$; the forget gate is $$f_{l}^{(i)}$$, the input gate is $$i_{l}^{(i)}$$; the output gate is $$o_{l}^{(i)}$$, the hidden state output is $$h_{l}^{(i)}$$; and the memory cell state is $$c_{l}^{(i)}$$. At the previous time $$t - 1$$, the cell state memory is $$c_{l-1}^{(i)}$$ and the hidden state output is $$h_{l-1}^{(i)}$$. The following equations describe the relationship between these variables.\textsuperscript{31,32}

\begin{equation}
f_{l}^{(i)} = \sigma \left( W_{f}^{(i)} [h_{l-1}, x_{l}] + b_{f}^{(i)} \right)
\end{equation}
\[ i_t^{(l)} = \sigma \left( W_i^{(l)} [h_{t-1}, x_t] + b_i^{(l)} \right) \]  
\[ c_t^{(l)} = \tanh \left( W_c^{(l)} [h_{t-1}, x_t] + b_c^{(l)} \right) \]  
\[ o_t^{(l)} = \sigma \left( W_o^{(l)} [h_{t-1}, x_t] + b_o^{(l)} \right) \]  
\[ c_t = i_t^{(l)} \cdot c_{t-1} + \gamma_t^{(l)} \cdot i_t^{(l)} - t_1 \]  
\[ h_t^{(l)} = o_t^{(l)} \cdot \tanh \left( c_t^{(l)} \right) \]  

Also shown in Figure 8 for schematic illustration, where \( W_a^{(l)} [h_{t-1}, x_t] \) (with \( a = \{i, f, c, o\} \)) are the weight matrices corresponding to different input vectors \( x_t \) or \( h_{t-1} \), respectively, within different gates. \( \gamma_t^{(l)} \) is a vector of candidate memory cells created by the \( \tanh \) function. \( \sigma \) and \( \tanh \) are the sigmoid and \( \tanh \) activation function, respectively.

### 3.2 Rolling window method for data preprocessing

The raw data cannot be fed into the proposed model directly because the LSTM neural network expects input or output sequences. The rolling window method is used to transform the raw data into \( X \) (input) and \( Y \) (output) sequences. In this method, \( \Delta t \) is defined as the rolling window size, and a series of small samples with the same number can be obtained by rolling through the whole sample with a fixed window size. Therefore, to predict the time series value at time \( t + 1 \), the rolling window feeds not only the value at time \( t \) but also those at times \( t - 1, t - 2, ..., t - \Delta t \) to the model. The predicted value at time \( t + 1 \) is appended to the sequence at time \( t + 1, t, t - 1, \)

### TABLE 4 The rolling window algorithm

**Algorithm 1 The Rolling Window Algorithm**

**Input:** A time series dataset \( D_T = \{T_1, T_2, T_3, ..., T_n\} \)

- Rolling window size \( \Delta t \)
- Min periods \( t \)
- Forecast horizon \( h \)

**Output:** The time series samples generated by rolling window algorithm

1. For \( D_T = \{T_1, T_2, T_3, ..., T_n\} \)
   1.1: For \( i \) in range (1, \( n \))
      - For \( \lambda_a = (1, \alpha) \), \( \eta_a = (1, \alpha) \)
        1.1.1: Starting with \( i \), Record data from \( T_i \) to \( T_{i+\Delta t} \)
        1.1.2: If \( i + \Delta t + h < n \)
        1.1.3: Save the array \( \{T_i, ..., T_{i+\Delta t}\} \) as the first input sequence \( \lambda_t \), and the array \( \{T_{i+\Delta t+1}, ..., T_{i+\Delta t+h}\} \) as the first output sequence \( \eta_t \).
        1.1.4: For \( \lambda_a, \eta_a \) in range (1, \( \alpha \))
        1.1.5: Rolling the window to the right, Record data from \( T_{i+\alpha} \) to \( T_{i+\alpha+\Delta t} \)
        1.1.6: If \( i + \alpha + \Delta t + h < n \)
        1.1.7: Save the array \( \{T_{i+\alpha}, ..., T_{i+\alpha+\Delta t}\} \) as the \( \alpha \) input sequence \( \lambda_a \), and the array \( \{T_{i+\alpha+\Delta t+1}, ..., T_{i+\alpha+\Delta t+h}\} \) as the \( \alpha \) output sequence \( \eta_a \).
        1.1.8: End If
   1.2: End For
2: End If

**Return:** The time series samples generated by rolling window algorithm

\[ t - 2, ..., t - \Delta t - 1, \] and so on until the last value has been predicted. This can be expressed as follows.

\[ f (x_t, x_{t-1}, x_{t-2}, ..., x_{t-\Delta t}) = x_{t+1} \] (11)

\[ f (x_{t+1}, x_t, x_{t-1}, x_{t-2}, ..., x_{t-\Delta t+1}) = x_{t+2} \] (12)
The algorithm of rolling window is shown in Table 4. Specifically, we assume 10 samples in the dataset, including T1, T2, ..., T10, and set $\Delta t = 6$. An example of the transformation of the raw data to time series samples is shown in Figure 9.34 The appropriate window size for the study will be identified later in Section 4.

3.3 Transfer learning

Traditional machine learning (supervised learning) relies on the availability of a large amount of labeled data and the identical distribution of the training and test data. However, the difference in data distribution and the lack of sufficient labeled data are challenges when tackling practical problems. Transfer learning, as opposed to traditional machine learning, uses the ability of a system to recognize and apply knowledge and skills learned in the source domains or tasks to new but related target domains or tasks. This is an important ability that enables solving the problems described above. Figure 10 shows the learning processes comparing traditional machine learning and transfer learning.

Given a source domain $D_S$ and a target domain $D_T$, transfer learning aims to help improve the target prediction performance using the transfer of knowledge in the source domain data when dealing with the issue of time series prediction but with few fresh training samples. Based on the definition of transfer learning and learning patterns, transfer learning can be divided into instance transfer, feature-representation transfer, relational-knowledge transfer, and parameter transfer. In this study, the parameter transfer approach is adopted, in which the parameters of hidden layers and the hyperparameters of the above pre-trained LSTM model act as initialization parameters of another LSTM model over the target domain data.

Some studies in engineering research have recently explored the applicability of deep learning techniques and transfer learning strategies. Li et al. proposed a model to predict dam displacement data based on transfer learning and deep learning. Transfer learning is used to transfer the knowledge learned from similar sensors to improve prediction accuracy in the target sensor. Ma et al. proposed a method that integrates transfer learning and advanced deep learning to transfer knowledge from existing air quality stations to new stations to predict air quality. For monitoring mining-induced stress, a set of stress sensors is usually installed in different sections. Along the mining direction, the longwall face passes through each monitoring section in turn. When the longwall face is going through a monitoring section, the stress sensor can record complete monitoring data successfully if the sensor does not early fail work. Therefore, according to transfer learning theory, the complete monitoring data of the adjacent stress sensor can be considered the source domain, and the monitoring data of the following stress sensor can be regarded as the target domain.

4 CASE STUDY

4.1 Data collection and preprocessing

A detailed analysis of a stress monitoring scheme and the results in a coal mine are presented in Section 2. To test the proposed model, the monitored vertical stress data from the field monitoring case of the Dongtan coal mine were used as an application study. The monitored vertical stress data of S-2 (Figure 5(A)) (Data acquisition time: 8 May 2019–15 June 2019) and S-3 (Figure 5(B)) (Data acquisition time: 14 June 2019–18 July 2019) are used as the source and target domain data, respectively. To avoid the influence of noise data on the model, we artificially eliminate some extremely outlier and inconsistent data and select the average of the data every 6 h as a data sample during the data collection process. However, the model cannot learn the full process of the stress variation because the data must be split into training and test datasets. To learn enough patterns and knowledge from the source domain time series, especially when the peak of stress is reached, the vertical stress data of S-2 are copied to augment the size of the dataset in source domain. This is reasonable because transfer learning only focuses on the performance of the target domain. Then, the rolling window method is used to transform the source domain data to time series samples and split the data into the training and test datasets in proportions of 90%–10%, respectively, to pre-train the base LSTM model.
4.2 | Performance evaluate indicators

To evaluate the performance of the proposed model, three widely used evaluation indicators, namely, root mean square error (RMSE), mean absolute percentage error (MAPE), and mean absolute error (MAE), are adopted to measure the prediction error of the model. The equations are described as follows:

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{13}
\]

\[
MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| 1 - \frac{\hat{y}_i}{y_i} \right| \tag{14}
\]

\[
MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{15}
\]

where \( n \) is the number of the prediction, and \( y_i \) and \( \hat{y}_i \) are the \( i \)th actual monitoring stress data and predicted value, respectively. \( \hat{y} = \frac{1}{n} \sum_{i=1}^{n} y_i \). Low values of the RMSE, MAPE, and MAE indicate high accuracy of the predictions.

4.3 | Determination of hyperparameters and network structure for base LSTM model

4.3.1 | Rolling window sizes

The size of the rolling window \( \Delta t \) influences the prediction performance. This is because data for previous instances might have a strong or weak lagged effect on the data at the next instance. A small window size cannot guarantee that enough information and sample features will be processed for the LSTM neural network inputs, while a large window size might increase unrelated information and, thus, the computation complexity.\(^{34,36}\) To determine an appropriate window size, the autocorrelation function\(^{37}\) is used to measure the temporal correlations among stress time series. Higher autocorrelation coefficients indicate stronger time correlations. For a window size \( \Delta t \), the autocorrelation functions can be calculated as follows:

\[
\rho_{\Delta t} = \frac{\text{Cov}(y(t), y(t + \Delta t))}{\sqrt{\text{Var}(y(t)) \cdot \text{Var}(y(t + \Delta t))}} \tag{16}
\]

where \( y(t) \) and \( y(t + \Delta t) \) denote the stress value at time \( t \) and \( t + \Delta t \), respectively. \( \text{Cov}(\cdot) \) represents the covariance, and \( \sigma(\cdot) \) is the standard deviation.
For the source domain data, Figure 11 shows the autocorrelation coefficients for different window sizes. The autocorrelation coefficients clearly decrease with increasing window size. This confirms that the earlier events have a weaker impact on the current status. In addition, when the window size is <7, the autocorrelation coefficient is >0.5. This study follows the range of the window size used in previous studies when the autocorrelation coefficients are >0.5, which indicate a high temporal correlation. However, for our stress data, the coefficients are >0.5 for a window size ≤7. To ensure enough sample features for model inputs, the window size \( \Delta t \) was therefore set as 7.

### 4.3.2 Learning rate and LSTM structure

In addition to the above rolling window sizes, the LSTM neural network structure and other hyperparameters influence the forecasting performance. To obtain an optimal prediction performance on the base LSTM model, the grid search method is used to optimize the hyperparameters. Given the premise of window size \( \Delta t = 7 \), the ranges of the learning rate (0.0001, 0.01), hidden layers (2, 3), hidden units (5, 100), and epoch times (200, 1000) were used to determine the optimal hyperparameters for the model. The evaluation criteria of the RMSE were used to measure the prediction performance for each parameter combination. In this base LSTM model, the Adam optimizer algorithm was used, which can replace the classic stochastic gradient descent method to update the network weights more effectively.

Table 5 shows the influence of the learning rate on performance. For the models using the four network structures, the prediction error increases significantly when the learning rate is 0.01 and decreases when the learning rate is <0.001. Therefore, the recommended learning rate for this model is <0.001. Figure 12 shows the prediction accuracy as a function of the different LSTM network structures and number of iterations (for learning rate = 0.0001). The different network structures provide considerable improvements to the prediction error of the LSTM models. The minimum prediction error is at around the 400th iteration. However, the fluctuations are caused by the inherent stochasticity in training or poor combination of parameters, which are usually observed in such cases, and cannot be completely eliminated. Therefore, for these hyperparameters (such as the learning rate of 0.0005 and 0.0001, and network structure as [20,10,5]), the amplitude and frequency of fluctuations can be reduced. Considering the above problems and learning efficiency, the learning rate, network structure, and epochs were set as 0.0001, [20,10,5], and 400 for the base LSTM model, respectively.

### 4.4 Analytical results and discussion

#### 4.4.1 Performance comparison between without transfer learning and with transfer learning

To verify the effect of the proposed model, the complete monitoring data of vertical stress of S-3 were considered to be the target domain data. The hyperparameters and
weights of the hidden layer of the pre-trained LSTM base model are transferred from the source domain data (vertical stress of S-2) to serve as initialization for the target LSTM model to be trained on the target domain data (vertical stress of S-3). It is assumed that the vertical stress data of S-3 are missing some data when the distance to the working face is approximately 33 m. Therefore, the monitored data closer than 33 m can be set as the training set, and all remaining data can be set as the test set. In addition, to compare the performance of the proposed model using the transfer learning method, another LSTM model without using transfer learning, and two time series prediction commonly used models, including Autoregressive Integrated Moving Average (ARIMA) and Recurrent Neural Network (RNN), are also used to generate predictions.

The predicted results without transfer learning (LSTM), with transfer learning, ARIMA, and RNN, are illustrated in Figures 13, 14, 15, and 16, respectively. The 95% confidence intervals calculated using multiple predictions are also shown in these figures. Given the prediction results of both cases, it can be seen from Figures 13, 15, and 16 that the variation of the predicted vertical stress tends to increase indefinitely when the transfer learning method is not used, and the peak of stress cannot be predicted. Figure 14 shows that it can be predicted accurately by the proposed method using transfer learning. This has important implications for the diagnosis and prognosis of rock bursts in coal mines. A comparison of the prediction error by three evaluation criteria is shown in Table 6, which shows that the predicted error without using transfer learning is 2–3 times greater than that obtained by the proposed method. This confirms that the use of the proposed method is more efficient than the use of the LSTM, ARIMA, and RNN model alone.

4.4.2 | Performance on different size of the target domain training data availability

In the actual monitoring application, the monitoring data may be lost at any time due to sensor failure, abnormal data transmission, or human factors. Therefore, the availability and amount of target domain data depends strongly on the practical situation and has a significant influence on the prediction results. To test the performance on different target domain training data sizes, six versions of the target domain training data were established. The target
domain training data were set at 50%, 55%, 60%, 65%, 70%, and 80% of the total target domain data, and the test set was assigned to all the remaining data. For each case, the same pre-trained LSTM model was used for transfer learning.

In addition, two metrics, which are RMSE and coefficient of determination ($R^2$), are adopt to describe the prediction performance on different size of the target domain training data availability of developed model. The RMSE has been defined in Section 3.4, and the $R^2$ can be calculated using the following equation:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \quad (17)$$

The results showed that, for each case, the stress peak and drop point can be predicted accurately using the transfer learning strategy. The stress drop points varied considerably; however, this was not important as the focus was on predictions of the buildup to the stress peak. The results of the RMSE and $R^2$-squared parameters as a function of size of the training data are shown in Figure 17.

Figure 17 shows that when the training data size was set to 50%, the prediction performance was poor. While the prediction performance improves significantly when the availability of the training data is 55%, the RMSE decreased from 7.21 to 3.48 MPa and the $R^2$ increased from 0.32 to 0.83. The fundamental reason for this trend is that the stress state was still in the virgin mode with no excavation disturbance at 66 m from the working face (training data availability 50%). The stress state is in an excavation disturbed zone at 54 m from the working face (training data availability 55%). As the training data size increases further, the prediction performance in terms of RMSE and $R^2$ values gradually improves. When the target domain training data availability is >65%, the RMSE value is <2 MPa and the $R^2$ is >0.9. This experiment demonstrates that the proposed model in this study is effective and can be used to predict the stress in future and recover the missing stress data when the target domain training data availability is >55%. In other words, the proposed model can significantly improve the prediction performance when the target domain training data availability has reached the stress disturbed zone.

5 | CONCLUSION

In this study, a framework that integrates an LSTM neural network and the transfer learning method to improve the prediction performance for missing stress data is proposed. To test the proposed model, vertical stress data of two monitoring sections obtained from previous field measurement for stresses in the Dongtan coal mine were selected as a case study for stress prediction. The main conclusions from this study are as follows.

For the base LSTM model, excellent prediction performance is obtained when the network structure is set as three layers comprising [20,15,5] cells and when the window size is 7 and the learning rate is 0.0001. Model application and experimental results showed that the proposed model using transfer learning is more efficient than a model without transfer learning. Moreover, the peak stress can be predicted accurately by the proposed model.

With the increase in the size of the target domain training data availability, the prediction performance measured by the RMSE and R-squared values improves. The proposed model can be used to predict the stress in future and recover missing stress data. The prediction
performance improves significantly when the target domain training data availability is >55%, indicating that the data have reached the stress disturbed zone. The main contributions of the proposed framework are that the LSTM neural network and transfer learning method are integrated to improve the mining-induced stress prediction performance when data are missing. This can be applied to reconstruct the missing data or predict the stress state in the next few days, which is crucial for the diagnosis and prognosis of the stability of surrounding rock, and provides an important reference for similar projects. However, in the mining field, many factors such as blasting, tremor generated by wave propagation, and energy release of the hard roof fracturing can cause sudden stress changes. The influence of these external factors on stress cannot be accounted for by the proposed model. This challenging and significant work will be carried out in future studies.

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CONFLICT OF INTEREST
We declare that we have no conflict, interest, and personal relationships with other people or organizations that can inappropriately influence our work.

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