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An EA-LSTM–COMSOL Coupled Inversion Framework for Pressure-Field Reconstruction in Coalbed Methane Reservoirs

Zehan Zhang ^{1,2}, Weiguo Liang ^{1,2,*}, Fengqi Guo ^{1,2} and Jiwei Yan ^{1,2}

¹ Key Laboratory of In-Situ Property-Improving Mining of Ministry of Education, Taiyuan University of Technology, Taiyuan 030024, China; 17631965118@163.com (Z.Z.); guofengqi0197@link.tyut.edu.cn (F.G.); yanjiwei@tyut.edu.cn (J.Y.)

² College of Mining Engineering, Taiyuan University of Technology, Taiyuan 030024, China

* Correspondence: liangweiguo@tyut.edu.cn

Abstract

Sparse underground pressure monitoring limits the direct characterization of full-field pressure distributions during coalbed methane (CBM) extraction, while conventional numerical simulations often require repeated parameter adjustments. This study proposes an intelligent inversion framework that couples an enhanced attention-based long short-term memory (EA-LSTM) model with a COMSOL-based forward model. Coal Seam No. 3 at Xinjing Mine was selected as the engineering case study. The vertical stress correction coefficient, reservoir pressure, extraction pressure, and initial permeability were treated as inversion parameters, while the working-face advance distance was introduced to represent the mining stage. A multiparameter sample library was constructed using an orthogonal design and segmented advance conditions, and pressure responses from five extraction boreholes were used as inversion constraints. The proposed model achieved a mean squared error of 0.013 and a coefficient of determination of 0.987, outperforming nine benchmark machine-learning and deep-learning models. The relative errors between the inverted and measured borehole pressures ranged from 0.41% to 5.07%, with a value of 1.84%. The coupled framework improves the efficiency of boundary-parameter identification and enables rapid reconstruction of pressure fields in a coalbed methane reservoir.

Keywords: deep learning; boundary-parameter identification; sparse monitoring; multi-borehole constraints; fluid–solid coupling

1. Introduction

Coalbed methane (CBM) is an important unconventional natural gas resource occurring in coal-bearing strata and has considerable development potential [1,2]. Efficient CBM extraction is not only essential for ensuring coal-mine safety, but also an important means of improving the comprehensive utilization of gas resources [3]. Among the controlling factors, the pressure distribution is a key indicator of reservoir state, evolution, and extraction efficiency. Accurately characterizing the spatiotemporal evolution of the pressure field during extraction is therefore crucial for optimizing borehole layouts, adjusting extraction parameters and identifying abnormal high-pressure zones [4].

In underground coal mines, pressure monitoring is constrained by testing costs, monitoring conditions, and construction environments. As a result, pressure data are often sparse, spatially discrete, and discontinuous, making it difficult to characterize the full

Received: 15 June 2026

Revised: 24 July 2026

Accepted: 27 July 2026

Published: 29 July 2026

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pressure distribution within the extraction zone. Coal-mine production is also highly dynamic, with extraction requirements and boundary conditions varying over time and space. Traditional parameter setting based on engineering experience and repeated adjustment of extraction schemes is therefore inadequate for refined identification and dynamic optimization under complex working conditions [5].

Previous studies have investigated the effects of reservoir conditions and engineering parameters on CBM extraction performance [6–8]. Reservoir conditions, including in situ stress, initial reservoir pressure, and permeability, govern the extent of pressure depletion and the gas-flow response during extraction [6,7]. Engineering parameters, such as extraction pressure, borehole diameter, borehole length, and pre-drainage duration, further regulate extraction intensity and long-term production performance [8]. Consequently, reservoir conditions determine the fundamental extraction environment, whereas engineering parameters provide the primary means of controlling and optimizing the extraction process.

Numerical simulation has been widely used to describe gas migration, pressure decline, and stress disturbance in coal and rock masses, supporting effective extraction-radius analysis, borehole-layout optimization, and extraction-parameter evaluation. Cheng et al. [9] used a gas–solid coupling model to investigate the role of extraction negative pressure and obtained gas-concentration responses under different extraction pressures. Wang et al. [10] and Zhang et al. [11] established gas–solid coupling models to simulate the evolution of the effective extraction radius under different engineering backgrounds and analyzed the effects of multiple factors. Specialized geological and reservoir-modeling approaches have also been applied to the three-dimensional characterization of CBM resources and to the simulation of gas–water flow considering adsorption and capillary trapping [12,13]. However, conventional numerical simulations usually involve numerous parameters and complex boundary conditions. Model calibration and parameter assignment still rely heavily on engineering experience and repeated trial calculations, resulting in low efficiency for multi-factor and multi-scenario analyses.

With the rapid development of artificial intelligence, data-driven methods have shown strong advantages in nonlinear modeling, pattern recognition, and intelligent decision-making, and have been increasingly applied to gas extraction [14]. For example, Wang et al. [15] developed an intelligent decision-making and control model for borehole negative pressure in a borehole-pipe-network system. Xue et al. [16,17] compared multi-objective random forest and multi-output regression-chain models for production prediction and sensitivity analysis. Ma et al. [18] used gradient-boosted decision trees for initial production prediction. Cheng et al. [19] constructed an LSTM-based prediction model and proposed a dynamic regulation strategy for extraction negative pressure. Zhao et al. [20] proposed a real-time identification and detection model suitable for underground scenarios. These studies demonstrate the strong potential of deep learning for high-dimensional, multi-source and nonlinear geoscience data [21,22].

Xinjing Mine is located in the western Yangquan Mining Area, Shanxi Province, northern China. Coal Seam No. 3 was selected as the target reservoir because it is one of the principal gas-bearing seams in the mine. Field investigations indicate that gas pressure varies spatially from approximately 0.4 to 2.4 MPa. Its relatively high gas pressure, low permeability, and heterogeneous pressure distribution make it a representative engineering case for pressure-field reconstruction under conditions of sparse underground monitoring and mining-induced disturbance [23,24].

Although significant progress has been made in numerical simulation, intelligent prediction and working-condition regulation, pressure-field reconstruction during CBM extraction remains insufficiently studied. The limited number of underground monitoring points cannot directly characterize a continuous pressure field; conventional numerical

simulation remains inefficient for parameter adjustment and scheme comparison under complex conditions; and the coupling between data-driven models and mechanism-based models still lacks sufficient engineering interpretability. Therefore, this study develops a cooperative inversion framework that integrates an intelligent model with mechanism-based constraints for pressure reconstruction during underground CBM extraction. The objective is to efficiently infer regional pressure distributions from sparse local monitoring data.

2. Methodological Framework for EA-LSTM-COMSOL Coupled Pressure-Field Inversion

The methodological framework integrates complementary data-driven techniques and physics-based modeling into a unified workflow developed for CBM pressure-field inversion and reconstruction. The residual-learning strategy was developed based on Refs. [25,26]; the baseline LSTM architecture followed the formulations and network structures reported in Refs. [27–30]; the particle swarm optimization (PSO) was implemented following Refs. [31–33]; and the temporal attention mechanism was constructed based on Refs. [34,35]. These individual components are established methods rather than original developments of the present study. The methodological contribution of this study lies in their problem-specific integration with mining-stage-aware sample organization, five-borehole pressure constraints, and a COMSOL-based forward model. The working-face advancing distance is introduced as an auxiliary variable representing the mining stage, enabling the model to learn the nonlinear relationship between boundary parameters and borehole pressure responses at different mining stages. A two-layer LSTM is adopted to extract correlations among adjacent samples, while the incorporation of an attention mechanism, residual connections, Dropout, and L2 regularization enhances feature extraction capability and training stability [25,26]. Particle swarm optimization (PSO) is used to optimize key hyperparameters, including the number of LSTM units, Dropout rate, batch size, learning rate, and the L2 regularization coefficient.

For this inversion problem, the samples are organized as a multi-input, multi-output sequential regression task. Unlike conventional long-term production time series, the training samples are constructed from mining advance stages and numerical simulation results. A sliding-window strategy is used to organize data from adjacent advancing stages, enhancing the model's ability to learn continuous pressure response evolution and avoiding the treatment of different mining stages as identical states.

To formalize the stage-dependent multi-input, multi-output sample organization adopted in this study, the input matrix and predicted output vector are defined as follows:

$$\mathbf{X}_t = [\mathbf{x}_{t-T+1}, \mathbf{x}_{t-T+2}, \dots, \mathbf{x}_t]^T \in \mathbb{R}^{T \times N} \quad (1)$$

$$\hat{\mathbf{y}}_t = f_{\theta}(\mathbf{X}_t) \in \mathbb{R}^M \quad (2)$$

where T is the sequence length (time-step length), N is the number of input features, and each of $\mathbf{x}_{t-T+1}, \mathbf{x}_{t-T+2}, \dots, \mathbf{x}_t \in \mathbb{R}^N$ represents the input-feature vector corresponding to a specific working-face advance stage. The input matrix $\mathbf{X}_t \in \mathbb{R}^{T \times N}$ contains the input features from T consecutive advance stages, with the rows representing the advance stages and columns representing the input features. The function $f_{\theta}(\cdot)$ denotes the trained EA-LSTM mapping with network parameters θ , and $\hat{\mathbf{y}}_t \in \mathbb{R}^M$ is the predicted pressure vector at the M extraction boreholes. Equations (1) and (2) define the stage-dependent input-output data structure used to organize the inversion samples in this study; they do not represent new formulations of the LSTM algorithm.

In this study, $T = 3$, that is, three consecutive advance-stage samples constitute one input sequence. The five input features are the working-face advance distance, vertical stress correction coefficient, reservoir pressure, extraction pressure, and initial permeability. The outputs are the pressure values at five extraction boreholes. A sequence length of three was selected because adjacent advance stages exhibit continuous pressure evolution, whereas a longer sequence would reduce the number of effective training samples and increase model complexity given the available dataset.

2.1. EA-LSTM Model and PSO

To evaluate the effectiveness of the proposed model-improvement strategy, a basic LSTM time-series inversion model is first constructed as the baseline model, with its network architecture shown in Figure 1a [27–30]. The model adopts a two-layer LSTM architecture. The first LSTM layer outputs the complete time sequence to extract dynamic features across multiple time steps, while the second LSTM layer further compresses the high-dimensional time-series features. Batch Normalization (BN) is introduced between the two LSTM layers to improve training stability, and a Dropout mechanism is applied at the output stage to mitigate overfitting. Finally, a fully connected layer performs the joint inversion of multiple target variables. The computational workflow of the baseline model can be summarized as follows: input sequence $\rightarrow$ LSTM feature extraction $\rightarrow$ feature compression $\rightarrow$ regularization $\rightarrow$ multi-output inversion. This model serves as a benchmark in subsequent comparative experiments to evaluate the performance improvements achieved through parameter optimization and architecture enhancement.

An LSTM-based architecture was selected instead of an autoencoding Transformer framework because of the structure and scale of the present dataset. Each input sequence consists of only three consecutive working-face advance stages, and the complete sample library comprises 525 numerical simulation cases. Consequently, the present task emphasizes short-range stage dependencies and nonlinear multi-output mapping rather than representation learning from long sequences. The recurrent structure of the LSTM provides an explicit inductive bias for preserving sequential information while requiring a relatively compact parameterization. By contrast, an autoencoding Transformer would introduce additional representation-learning and optimization complexity that is difficult to justify given the short-sequence length and limited sample size. Nevertheless, a conventional Transformer was retained as a benchmark model, and the comparative results presented in Section 3.1 further demonstrate the suitability of the LSTM-based architecture for the present inversion task.

The inversion performance depends strongly on network structural parameters and training hyperparameters. To reduce the uncertainty associated with manual parameter selection, particle swarm optimization (PSO) is incorporated into the model-training workflow. In this framework, PSO does not directly solve the CBM pressure field but functions as a hyperparameter optimization tool. Each particle represents a parameter configuration, including the number of neurons in the two LSTM layers, Dropout rate, batch size, learning rate, and L2 regularization coefficient. For each particle, a corresponding LSTM network is trained, and the validation-set mean squared error (MSE) is used as the fitness function.

The overall workflow of PSO–LSTM parameter optimization is shown in Figure 1b, including particle initialization, model construction, model training, validation-set evaluation, and particle velocity and position updates. Through iterative multi-generation search, the algorithm gradually converges toward the global optimum in the parameter space, yielding model configurations with improved performance and stronger generalization capability. This framework provides a unified hyperparameter search basis for the

subsequent enhanced LSTM models incorporating attention mechanisms, without altering the core inversion architecture.

Based on the baseline model and the parameter optimization framework described above, an Enhanced Attention-LSTM (EA-LSTM) model is further developed. By dynamically assigning attention weights, the model enables the network to focus on critical time-step information during sequence processing, thereby enhancing its ability to capture pressure response characteristics [34,35], as illustrated in Figure 1c.

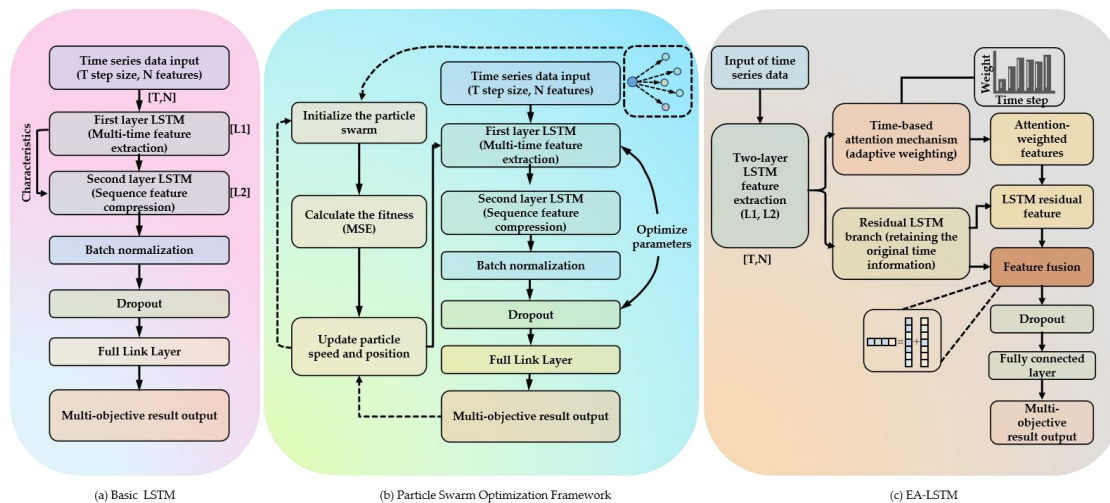


Figure 1. Network structure diagram: (a) basic LSTM; (b) Particle Swarm Optimization Framework; (c) EA-LSTM. Solid arrows indicate the main data flow, whereas dashed arrows indicate iterative feedback or auxiliary feature connections.

A temporal attention mechanism is incorporated into the two-layer LSTM feature-extraction framework. The output sequence of the second LSTM layer is fed into an attention module to generate a temporal weight distribution. Features from different time steps are then weighted and aggregated to obtain a temporal representation that emphasizes the most informative pressure response patterns. To reduce the potential loss of historical information caused by attention weighting, a residual LSTM branch is introduced in parallel to preserve the original temporal features. The attention-enhanced representation and the residual branch output are then fused and passed through Dropout and a fully connected layer for multi-target inversion. This enhanced architecture preserves the temporal modeling capability of the LSTM while explicitly capturing the relative importance of different time steps, thereby improving inversion accuracy and stability under dynamic pressure-field conditions.

2.2. Pressure-Field Inversion Strategy Coupled with COMSOL

2.2.1. Principles of Inversion

Parameter inversion is essentially an inverse problem whose objective is to determine the key parameters characterizing a system from observational data or response relationships. This process requires that the forward problem be solvable. It begins with the construction of a forward computational model describing the physical phenomenon, followed by the derivation of the corresponding solution. Mathematically, parameter inversion is generally formulated as an optimization problem that minimizes an objective function under given constraints. The objective function quantifies the discrepancy between the observed data vector and the model-calculated responses [36]. Therefore, the inversion quality depends on the accuracy of the forward model, the reliability of the observed data,

and the effectiveness of the optimization algorithm. The parameter inversion problem can be expressed as follows:

$$\min \{J(\mathbf{m}, \mathbf{d}_m)\}, \mathbf{m} \in R^p, \mathbf{d}_m \in R^m, g^j(\mathbf{m}) \leq 0 \quad (3)$$

where $\mathbf{m}$ is the parameter vector to be inverted, R^p is the parameter space, $\mathbf{d}_m$ is the observation (or experimental) data vector, and R^m is the data space. The function $g^j(\mathbf{m})$ denotes the j -th inequality constraint in the general constrained inverse-problem formulation. In the present study, no additional nonlinear physical constraints were introduced. Instead, the constraints were imposed through the lower and upper bounds of the inverted parameters, as expressed in Equation (5).

During the parameter optimization, the discrepancy between the observed or predicted data can be measured using a norm. A typical objective function is written as:

$$J(\mathbf{m}) = (\mathbf{d}_m - \mathbf{d}_c(\mathbf{m}))^T \omega (\mathbf{d}_m - \mathbf{d}_c(\mathbf{m})) \quad (4)$$

where ω is the weighting matrix, reflecting the influence of measurement accuracy on inversion results, and $\mathbf{d}_c(\mathbf{m})$ is the model-predicted data vector as a function of the inverted parameters.

Accordingly, the parameter inversion problem can be formulated as follows:

$$J(\mathbf{m}) \rightarrow \min; m_l \leq m \leq m_u \quad (5)$$

where m_l and m_u denote the lower and upper bounds of the parameter space, respectively.

Equations (3)–(5) follow the constrained parameter-inversion formulation adopted in Ref. [36]. In the present study, the parameter vector consists of the vertical stress correction coefficient, reservoir pressure, extraction pressure, and initial permeability; the observation vector consists of the measured pressures at the five extraction boreholes; and the lower and upper bounds of the parameter vector parameter bounds are defined according to the ranges used in the numerical sample library. Thus, the general constrained inversion formulation is adapted to the specific CBM pressure-field reconstruction problem considered in this study.

2.2.2. Inversion Steps

The distribution of the coalbed methane (CBM) pressure field is closely related to the advancement of the coal mining face. Under complex geological conditions, the CBM pressure field exhibits strong spatial heterogeneity, while measured borehole pressure data are often discrete. The main challenge of pressure-field inversion is to establish the nonlinear relationship between the global pressure distribution and the limited pressure observations obtained from boreholes. Therefore, this study employs intelligent algorithms to construct a surrogate mapping model between the boundary conditions of a three-dimensional numerical model and the pressure responses at production wells. The workflow is as follows:

- ① Establish a three-dimensional geological model based on the site conditions.
- ② Define multiple sets of boundary parameter combinations, perform simulations in COMSOL Multiphysics 5.6, and obtain CBM extraction-well pressure values under different boundary conditions.
- ③ Extract the simulated pressure values at the CBM production wells corresponding to the measurement points for each parameter set to construct the training dataset, in which the inputs are the model boundary parameters and the outputs are the pressure responses at the measurement points.

- ④ Used the constructed dataset to train the EA-LSTM model and establish the nonlinear mapping between boundary parameters and borehole pressure responses.
- ⑤ The PSO procedure follows Refs. [31–33]. For the five-borehole-constrained inversion, a least-squares objective (fitness) function is defined to quantify the discrepancy between the borehole pressures predicted by the EA-LSTM model and the corresponding measured pressures:

$$S(x_1, x_2, \dots, x_k) = \min \left\{ \frac{1}{k} \sum_{i=1}^k [T_i(x_1, x_2, \dots, x_k) - R_i]^2 \right\} \quad (6)$$

where k is the number of selected observation points, T_i is the value at the i th point from the hybrid neural-network model, and R_i is the corresponding value.

- ⑥ Generate new combinations of boundary parameters and input them into the trained EA-LSTM model established in Step ④ to predict the CBM extraction-well pressures at the measurement locations. Compare the predicted and measured pressures, evaluate the PSO fitness function, and iteratively determine the optimal boundary parameters.
- ⑦ Apply the optimized boundary parameters to the three-dimensional COMSOL numerical model to simulate the spatial distribution of the CBM reservoir field.
- ⑧ Repeat steps ①–⑦ to obtain the dynamic evolution model of the coalbed methane pressure field. The flowchart is shown in Figure 2.

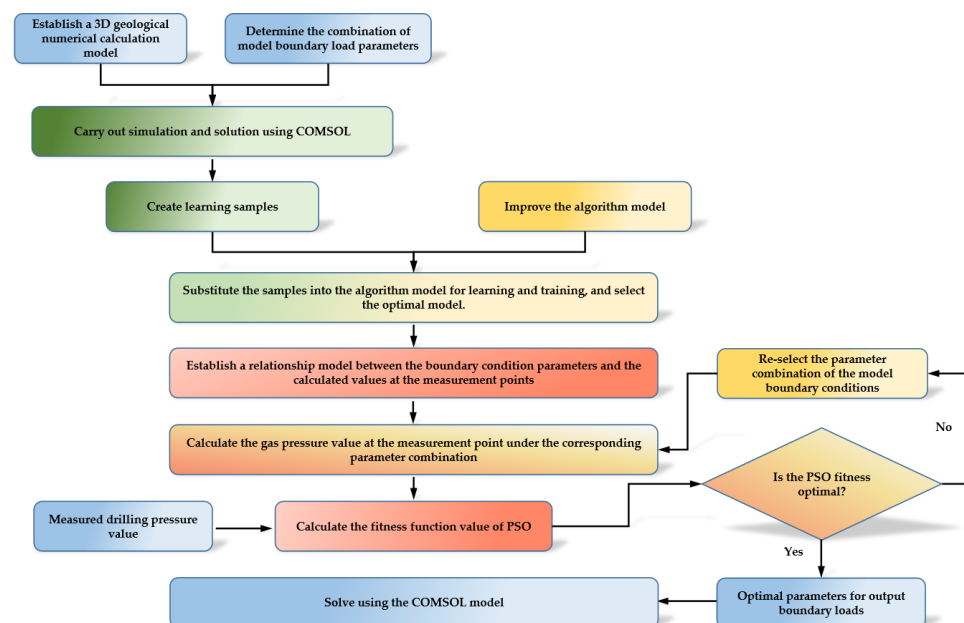


Figure 2. Inversion flowchart. Arrows indicate the workflow direction and iterative feedback; the background colors distinguish procedural modules and have no quantitative meaning.

2.3. Engineering Geological Background, Numerical Model Construction, and Sample Library Development

2.3.1. Engineering Geological Background and Data Sources

Xinjing Mine is located in the western part of the Yangquan Mining Area, Shanxi Province, China, between 113°21′10″–113°31′17″ E and 37°51′07″–37°56′31″ N (Figure 3a), covering an area of approximately 64.75 km². The mine has a designed production capacity of 5.8 Mt/year. The study area is underlain by Carboniferous–Permian coal-bearing strata, with the Taiyuan and Shanxi formations constituting the principal coal-bearing sequences. Mining is conducted at two production levels. Coal Seam No. 3 and No. 15 are

laterally continuous, stable, and largely recoverable, with Coal Seam No. 3 containing relatively high coalbed methane (CBM) resources [37–39]. The gas-pressure data and pressure-contour map used in this study were obtained from the gas-geological survey records of Xinjing Mine [23,24]. The measured gas pressure in the Coal Seam No. 3 ranges from 0.4 to 2.4 MPa, and its spatial distribution is shown in Figure 3b. A continuous initial pressure field was generated by spatial interpolation of the measured gas-pressure data. To simulate CBM extraction at the engineering scale while minimizing boundary effects associated with the finite model domain, a pressure-replenishment boundary was imposed around the coal-seam model to represent the continuous gas supply from the surrounding reservoir.

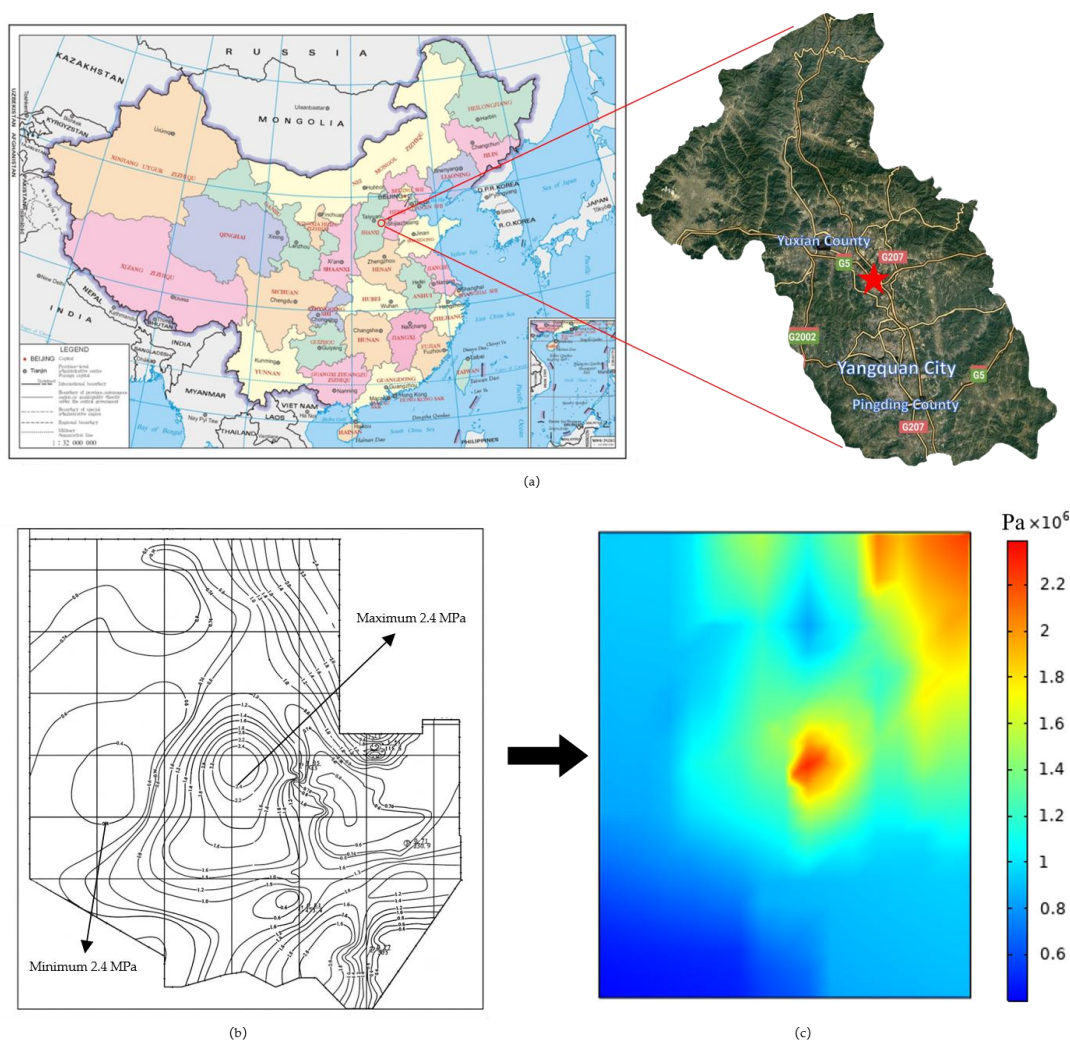


Figure 3. Geographical location map and coalbed methane (CBM) pressure distribution of Coal Seam No. 3: (a) location map; (b) measured CBM pressure contour map of Coal Seam No. 3; (c) interpolated pressure field used in the numerical simulation.

A three-dimensional multilayer geological model was established in COMSOL Multiphysics based on the geological data from Xinjing Mine, with Coal Seam No. 3 selected as the target CBM reservoir. The initial CBM pressure distribution adopted in the numerical model is shown in Figure 3c. Coal Seam No. 3 has an average thickness of 3 m and an average dip angle of approximately 5° . Because of its gentle dip, the coal seam was approximated as horizontal in the numerical simulation. The mechanical and seepage properties assigned to the coal seam and surrounding rock layers are listed in Table 1 [40,41]. The elastic modulus, Poisson's ratio, density, porosity, and initial permeability of Coal

Seam No. 3 were primarily determined from laboratory tests performed on coal samples collected from Xinjing Mine. The corresponding properties of the surrounding strata, including sandstone, mudstone, sandy mudstone, limestone, and Coal Seam No. 15, were obtained from published data for comparable lithologies [40,41]. Because the present study focuses on pressure-field inversion in Coal Seam No. 3, the properties of the surrounding strata were used primarily to represent the mechanical and seepage constraints of the multilayer geological system rather than as inversion variables.

Table 1. Basic mechanical parameters of coal and rock.

Rock	Thick- ness/m	Poisson's Ratio	Elastic Modu- lus/ 10^9 Pa	Biot	Porosity	Permeability/ 10^{-15} m ²	Density/kg·m ⁻³
Medium-grained sandstone	23	0.29	8.2	0.84	0.27	93.43	2410
Shale	50	0.21	4.1	0.61	0.25	0.12	2080
Fine sandstone	18	0.25	9.74	0.25	0.21	81.80	2510
Sandy mudstone	17	0.22	3.5	0.70	0.29	8.01	2100
Medium-grained sandstone	64	0.29	8.2	0.84	0.27	93.43	2410
No. 3	3	0.27	1.65	0.27	0.30	0.0324	1430
Shale	12	0.21	4.1	0.61	0.25	0.12	2080
Fine sandstone	20	0.25	9.74	0.25	0.21	81.80	2510
Sandy mudstone	24	0.22	3.5	0.70	0.29	8.01	2100
Fine sandstone	20	0.25	9.74	0.25	0.21	81.80	2510
Sandy mudstone	24	0.22	3.5	0.70	0.29	8.01	2100
Shale	15	0.21	4.1	0.61	0.25	0.12	2080
Limestone	14	0.20	10	0.78	0.27	70.02	2770
No. 15	10	0.18	2.3	0.58	0.21	0.10	1600
Shale	35	0.21	4.1	0.61	0.25	0.12	2080
Medium-grained sandstone	20	0.29	8.2	0.84	0.27	93.43	2410
Shale	35	0.21	4.1	0.61	0.25	0.12	2080

Lithological heterogeneity was represented by assigning different mechanical and seepage properties to the predefined geological layers. The measured initial CBM pressures were mapped onto the coal-seam domain by spatial interpolation to generate a continuous initial pressure field. The porosity and permeability values listed in Table 1 were used as initial values and were dynamically updated according to the local pressure and deformation during the coupled simulation. Consequently, the model accounts for both property contrasts among lithological layers and the spatiotemporal evolution of the reservoir properties.

COMSOL Multiphysics was selected because the present study requires customized coupling among gas seepage, coal deformation, permeability evolution, borehole pressure boundary conditions, and staged working-face advancement. Specialized geomodeling platforms, such as Petrel and GOCAD, provide powerful capacities for detailed geological reconstruction and geostatistical property modeling. In contrast, COMSOL provides greater flexibility for implementing the customized multiphysics coupling and mining-stage-dependent boundary conditions required by the proposed inversion framework.

2.3.2. Numerical Model Construction and Boundary Conditions

Based on the geological conditions of the Xinjing Mine, a numerical simulation model was established, with dimensions of 1000 m × 800 m × 395 m. For the mechanical boundaries, normal displacement constraints were applied to the four lateral boundaries and the bottom of the model, while a uniformly distributed load, representing the overburden pressure under gravitational conditions, was applied at the top.

For the flow boundaries, non-recharge boundaries were defined as no-flow boundaries, whereas pressure-recharge boundaries were set around the continuous gas recharge from large-scale external sources. The walls of the extraction boreholes were assigned constant-pressure boundaries to simulate the negative pressure induced by continuous field extraction.

To reflect the characteristics of multi-layer extraction, the initial model considered the diffusion of coalbed methane from Coal Seam No. 3 into adjacent reservoirs, including mudstone and sandstone. Both the CBM extraction process and the longwall mining advance were simulated using this initial model.

At the engineering scale, geological heterogeneity was represented by assigning different mechanical and seepage properties to the predefined lithological layers listed in Table 1. Consequently, the numerical model is heterogeneous at the lithological-layer scale. Within each lithological unit, however, the coal seam and surrounding rocks were treated as equivalent homogeneous and isotropic porous media [42,43]. This assumption reduces the number of material parameters and the computational cost, which is important because repeated forward simulations are required for sample-library generation and parameter inversion. Nevertheless, actual coal seams commonly exhibit transverse isotropy owing to bedding, cleat systems, and preferentially developed fracture networks [43,44]. Therefore, the present model does not explicitly account for directional variations in elastic stiffness or permeability, and the reconstructed pressure and stress fields should be interpreted as equivalent isotropic responses under the investigated engineering conditions.

To reduce the influence of non-unique (equivalent) solutions during parameter inversion, the inversion constraints were defined by combining advancement-stage constraints with multi-well pressure constraints. The pressure measurements from the five boreholes characterize the local pressure responses at different spatial locations, whereas the working-face advance distance defines the corresponding stage of mining disturbance. By incorporating the advance distance into the inversion framework, the algorithm identifies boundary-parameter combinations that are valid for a specific mining stage, thereby preventing pressure responses associated with different advance stages from being misinterpreted as the same reservoir state. This strategy reduces the occurrence of equivalent solutions and improves the uniqueness of the inversion results.

Previous studies have shown that when the final position of a production borehole is located within the middle or lower part of the fractured zone, the surrounding rock mass remains relatively stable, while the well-developed fracture network promotes CBM accumulation, thereby enhancing extraction efficiency [45]. In contrast, when the borehole terminates within the caving zone or the bending subsidence zone, extraction efficiency decreases because of borehole damage and poor permeability.

The overlying strata above Coal Seam No. 3 in the Xinjing Mine consist predominantly of medium-hard roof rocks. Therefore, the empirical relationships reported in Ref. [46] for medium-hard overburden conditions were adopted to provide a preliminary estimate of maximum heights of the caving and fractured zones. The corresponding empirical equations are given as follows:

$$H_k = \frac{100 \sum M}{4.7 \sum M + 19} + 2.2 \quad (7)$$

$$H_d = \frac{100 \sum M}{1.6 \sum M + 3.6} + 5.6 \quad (8)$$

where H_k is the maximum height of the caving zone (m); H_d is the maximum height of the fractured zone (m); $\sum M$ is the average mining height (m).

Equations (7) and (8) are empirical relationships established from comparative analyses of extensive field observations, in which the mining thickness and roof lithology were identified as principal factors controlling the development heights of the caving and fractured zones. Accordingly, the empirical equations for medium-hard overburden were adopted in this study. Positive correction terms of +2.2 m and +5.6 m were applied to estimate the maximum heights of the caving and fractured zones, respectively. These empirical coefficients are primarily applicable to medium-hard overburden conditions and should be verified before being applied to other mining settings.

Calculations indicate that the maximum heights of the caving and fractured zones are 11.3 and 41.5 m, respectively. Based on the zoning characteristics of the overlying strata, the interval located 11.3–41.5 m above the coal-seam roof corresponds to the fractured zone. For engineering design, the fractured zone was divided into four equal intervals, and the midpoint of the lower-middle interval, approximately 18 m above the coal-seam roof, was selected as the target depth for the gas drainage boreholes. Accordingly, the final numerical model and borehole layout of the boreholes are shown in Figure 4.

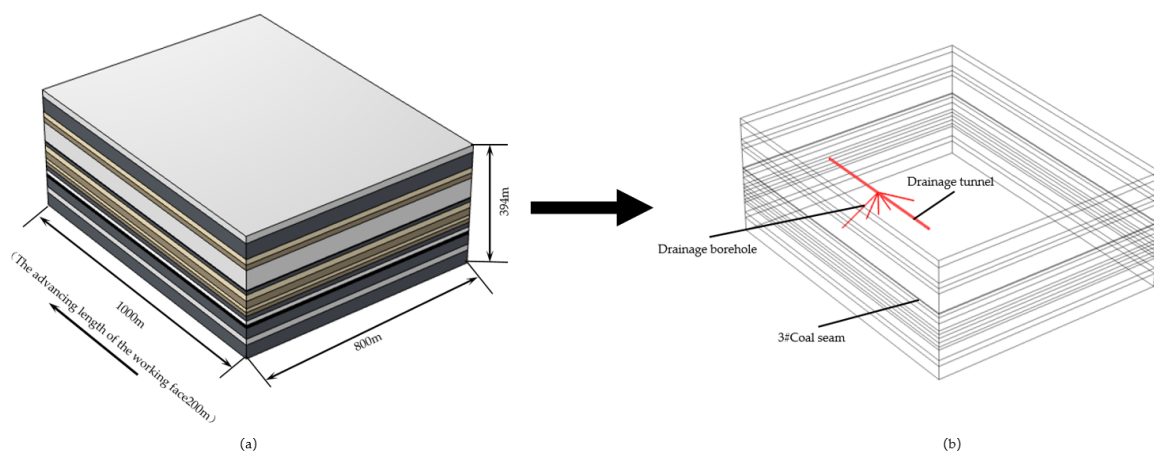


Figure 4. Three-dimensional geological model of the Xinjing Mine and borehole layout: (a) three-dimensional geological model; (b) borehole layout diagram.

The governing equations for gas flow and coal deformation were solved using the standard physics interfaces available in COMSOL Multiphysics. These built-in governing equations were adopted without modification and are therefore not reproduced here. The model-specific implementation focuses on the dynamic updating of coal-seam porosity and permeability in response to pore-pressure variations, adsorption–desorption strain, and coal deformation. Accordingly, only the constitutive relationships governing this coupled process are presented below.

The evolution of the coal-seam porosity, considering the coupled effects of volumetric deformation, pore-pressure variation, and adsorption–desorption, can be expressed as follows [47]:

$$\phi = 1 - \frac{1 - \phi_0}{1 + \varepsilon_v} \left[1 - K_v \Delta p + \frac{\varepsilon_a}{1 - \phi_0} \right] \quad (9)$$

where ϕ_0 is the initial porosity (dimensionless); ε_v is the volumetric strain (dimensionless); Δp is the change in pore pressure relative to the initial state (Pa). K_y is the bulk compressibility coefficient (Pa⁻¹) and the adsorption–desorption strain ε_a (dimensionless) are expressed as follows:

$$K_y = \frac{3(1-2\nu)}{E} \quad \varepsilon_a = \frac{2a\rho_c RTK_y}{3V_m} \ln(1+bp) \quad (10)$$

where E is Young's modulus of the coal rock (Pa); ν is Poisson's ratio (dimensionless); a and b are the Langmuir adsorption constants, where a is the Langmuir volume constant (m³·kg⁻¹) and b is the Langmuir pressure constant (Pa⁻¹); ρ_c is the density of the coal rock (kg·m⁻³); R is the universal gas constant (J·mol⁻¹·K⁻¹); T is the temperature (K), and V_m is the molar volume of the gas (m³·mol⁻¹).

The permeability evolution is described using the cubic law [48]:

$$\frac{k}{k_0} = \left(\frac{\phi}{\phi_0}\right)^3 \quad (11)$$

where k and k_0 are the current and initial permeabilities, respectively (m²).

The numerical model was discretized using a free tetrahedral mesh. Because the regions surrounding the production boreholes and roadways are characterized by stress concentrations, steep CBM pressure gradients, and significant variations in seepage velocity, local mesh refinement was applied around the boreholes and main roadways (Figure 5c). In contrast, relatively coarse elements were used in boundary regions far from the drainage boreholes and mining-affected zones (Figure 5b) to balance computational accuracy and efficiency.

During the solution process, a steady-state analysis was first performed to obtain the initial stress field and CBM pressure distribution. These steady-state results were then used as the initial conditions for the subsequent drainage and mining-advance simulations, and forward calculations were carried out under different combinations of boundary parameters.

In the numerical implementation, gas flow was simulated using the Darcy's Law interface, whereas coal deformation was solved using the Solid Mechanics interface. The pore pressure obtained from the gas-flow simulation was incorporated into the effective-stress calculation of the coal mass. The resulting volumetric strain, together with the adsorption–desorption strain, was used to update the porosity according to Equation (9), after which the permeability was updated using Equation (11). The updated permeability was then fed back into the gas-flow calculation, thereby establishing a two-way coupling between gas flow and coal deformation.

A stationary analysis was first conducted to determine the initial stress and CBM-pressure fields. These results were then used as the initial conditions for the time-dependent simulations of gas extraction and working-face advancement. The forward model was subsequently executed under different combinations of boundary parameters to calculate the pressure responses at the five extraction boreholes, thereby generating the sample library for the subsequent inversion analysis.

The influence of the global mesh density was first evaluated while maintaining the same locally refined mesh around the boreholes and roadways. Increasing the global mesh density from the coarse to the normal setting increased the number of elements from 115,298 to 206,995 and the number of degrees of freedom from 624,512 to 1,123,784. However, the mean and maximum relative differences in the calculated pressures at the five extraction boreholes were only 0.938% and 1.332%, respectively. These results indicate

that the relatively coarse far-field mesh has a negligible influence on the predicted borehole-pressure responses while substantially reducing the computational cost of repeated forward simulations.

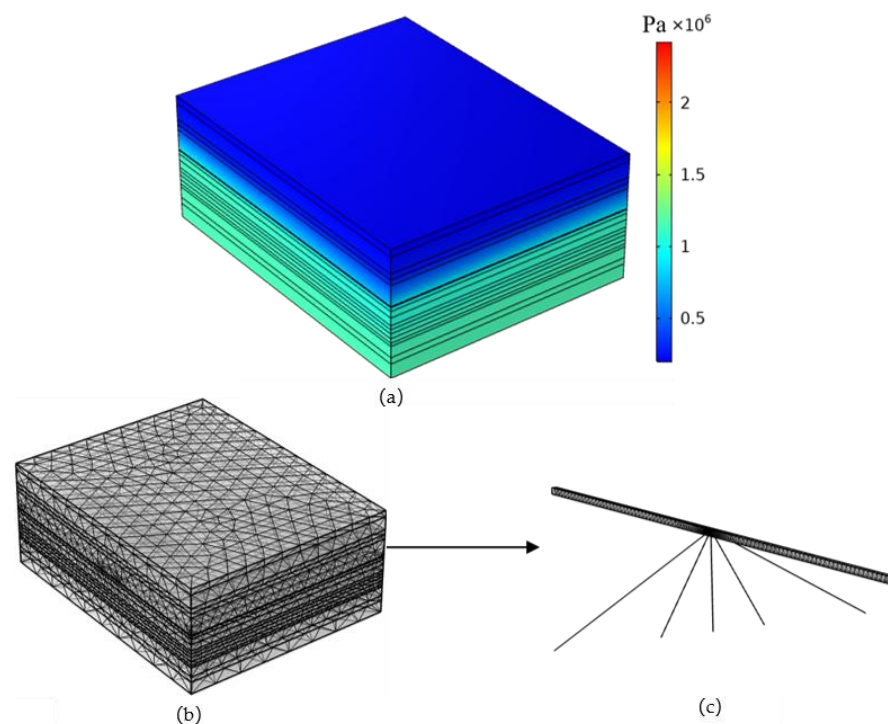


Figure 5. Numerical model results and mesh discretization: (a) initial coalbed methane (CBM) pressure distribution; (b) overall mesh discretization; (c) local mesh refinement around the extraction boreholes.

A further mesh-independence analysis was conducted using the normal global mesh while applying fine, finer, and extra-fine local meshes around the extraction boreholes and roadways. The three mesh configurations contained 193,412, 206,995, and 281,870 elements, corresponding to 1,056,492, 1,123,784, and 1,479,348 degrees of freedom (DOFs), respectively (Table 2). Taking the extra-fine mesh as the reference solution, the mean and maximum relative differences obtained with the finer local mesh were 1.373% and 1.828%, respectively. Further local refinement increased the number of elements and DOFs by 36.17% and 31.64%, respectively, whereas the maximum pressure difference remained below 2%. Therefore, the normal global mesh combined with the finer local mesh was adopted for all subsequent simulations to achieve an appropriate balance between numerical accuracy and computational efficiency.

Table 2. Mesh-independence analysis of the numerical model.

Global Mesh Scheme	Local Mesh	Elements	DOFs	Mean Difference (%)	Maximum Difference (%)
Coarse	Fine	193,412	1,056,492	2.275	3.295
Normal	Finer	206,995	1,123,784	1.373	1.828
Fine	Extra fine	281,870	1,479,348	/	/

2.3.3. Inversion-Parameter Design and Sample Library Development

The key to CBM pressure-field inversion is to establish a nonlinear mapping between the boundary parameters of the three-dimensional numerical model and the pressure responses at the CBM production wells. The proposed inversion framework is based on the

COMSOL numerical model and the training of the EA-LSTM algorithm. Consequently, the selection of representative boundary-parameter combinations is critical, as it directly affects the quality of the training dataset and, ultimately, the accuracy of the reconstructed pressure field.

The vertical stress correction coefficients, reservoir pressure, extraction pressure, and initial permeability were selected as the inversion parameters. These four parameters represent the in situ stress state, the initial reservoir conditions, the engineering extraction intensity, and the coal-mass permeability, respectively. They are the principal factors controlling the distribution of the CBM pressure field at extraction boreholes. Therefore, they were adopted as the boundary parameters to be inverted in the COMSOL numerical model.

Based on field measurement data from the mine, the parameter ranges were defined as follows: vertical stress correction coefficient $\alpha \in [0.63, 0.96]$, reservoir pressure $P_0 \in [0.40, 2.40]$ MPa, extraction pressure $P_k \in [15, 35]$ kPa, and initial coal-seam permeability $k \in [10^{-17}, 10^{-16}]$ m². To ensure the scientific validity and representativeness of the model boundary-condition samples, an orthogonal experimental design was adopted to generate 25 simulation scenarios with different parameter combinations (Table 3).

Table 3. Parameter combinations.

No.	Correction Factor	Reservoir Pressure (MPa)	Drainage Pressure (kPa)	Initial Permeability (10^{-17} m ²)
1	0.71	0.90	30.00	3.25
2	0.95	0.40	20.00	3.25
3	0.87	0.40	25.00	5.50
4	0.63	0.90	35.00	5.50
5	0.79	0.40	30.00	7.75
6	0.71	1.40	25.00	7.75
7	0.87	0.90	20.00	10.00
8	0.95	0.90	15.00	7.75
9	0.95	1.90	30.00	5.50
10	0.87	1.90	35.00	7.75
11	0.79	1.90	15.00	10.00
12	0.71	1.90	20.00	1.00
13	0.71	0.40	35.00	10.00
14	0.87	1.40	15.00	3.25
15	0.63	1.40	30.00	10.00
16	0.63	0.40	15.00	1.00
17	0.79	0.90	25.00	1.00
18	0.95	2.40	25.00	10.00
19	0.63	1.90	25.00	3.25
20	0.79	2.40	35.00	3.25
21	0.71	2.40	15.00	5.50
22	0.87	2.40	30.00	1.00
23	0.95	1.40	35.00	1.00
24	0.63	2.40	20.00	7.75
25	0.79	1.40	20.00	5.50

A segmented working-face advancement simulation strategy was adopted to construct the inversion sample database. Starting from an advancement distance of 0 m, each of the 25 boundary-parameter sets was simulated at 10 m advancement intervals. This generated a total of 525 numerical cases over an advancement range of 200 m. For each

parameter set, the corresponding gas pressures at the five drainage boreholes were extracted from the COMSOL simulations to construct the initial sample database containing 525 samples. To ensure that the dataset adequately represented pressure responses at different mining stages, the samples at each 10 m advancement interval were randomly divided into a training set (70%, 368 samples) and a test set (30%, 157 samples). This stratified partitioning improves the reliability and robustness of the subsequent model training and validation.

2.4. Problem-Specific Construction of the EA-LSTM Inversion Model

Unlike a conventional LSTM-based prediction workflow, the EA-LSTM model developed in this study was specifically designed for boundary-parameter inversion under stage-dependent mining conditions. Its methodological contribution lies not in the individual use of LSTM, temporal attention, residual learning, or PSO, but in their problem-specific integration with mining-stage-aware sample organization, multi-borehole pressure constraints, and COMSOL-based pressure-field reconstruction.

Specifically, the working-face advancement distance was introduced as an explicit mining-stage variable, and numerical samples from adjacent advancement stages were reconstructed as sequential inputs. A parallel temporal-attention and residual-LSTM architecture was then employed to extract stage-sensitive features while preserving the original sequential information. In addition, the pressures at five spatially distributed extraction boreholes were jointly predicted and used as constraints for boundary-parameter identification. The model construction and inversion procedures are summarized below.

Mining-stage-based data preprocessing and stratified sampling. The numerical samples were stratified according to the working-face advancement distance to ensure that different mining stages were proportionally represented in both the training and test sets. The input variables included the working-face advancement distance, vertical stress correction coefficient, reservoir pressure, extraction pressure, and initial permeability, whereas the target variables were the pressure responses at the five extraction boreholes. Because these variables have different physical dimensions and numerical ranges, all inputs were standardized before model training. The standardization parameters computed from the training set were subsequently applied to the validation and test sets. A validation subset was separated from the training data and used exclusively for hyperparameter optimization and early stopping, whereas the independent test set was reserved for the final performance evaluation.

Mining-stage-aware sequence reconstruction. The COMSOL simulations do not generate continuous production time series but discrete numerical cases corresponding to different combinations of boundary parameters and working-face advancement stages. Treating these samples as independent observations would neglect the continuity of pressure evolution during mining. Therefore, the samples were ordered according to the working-face advancement distance, and a sliding window of length three was used to construct the sequential inputs. Each input sequence contained information from three consecutive advancement stages, and the corresponding output was the five-component borehole-pressure vector at the target stage. By combining the advancement with adjacent-stage sequence reconstruction, the model distinguishes pressure responses associated with different stages of mining disturbance rather than treating them as equivalent reservoir states.

Parallel temporal-attention and residual-LSTM feature extraction. Based on a two-layer LSTM encoder, the output sequence of the second LSTM layer was processed through two parallel branches. In the temporal-attention branch, adaptive weights were assigned to the hidden states corresponding to different advancement stages, enabling the model to emphasize the stages that contributed most strongly to the current borehole-

pressure response. Because attention weighting may weaken part of the original sequential information, a residual-LSTM branch was introduced in parallel to preserve the unweighted temporal representation. The attention-weighted and residual features were subsequently fused and passed through a Dropout layer and a fully connected layer to jointly predict the pressures at the five extraction boreholes. Compared with a conventional stacked LSTM, the proposed architecture combines the selective extraction of stage-sensitive information with the preservation of the original temporal features.

Two-stage PSO-based hyperparameter optimization. To reduce the uncertainty associated with manually selected network hyperparameters, PSO was used to optimize the number of neurons in the EA-LSTM model, including the number of neurons in each LSTM layer, the Dropout ratio, batch size, learning rate, and the L2 regularization coefficient. A two-stage global-to-local optimization strategy was adopted. During the first stage, a relatively broad search space was explored to identify promising regions, whereas the second stage refined the search around the best solution obtained during the first stage. For each particle, an EA-LSTM model was constructed and trained, and the validation-set mean squared error (MSE) was used as the fitness function. The PSO procedure in this stage was used exclusively for neural-network hyperparameter optimization and is distinct from the subsequent PSO-based inversion of the physical boundary parameters in the COMSOL model.

Multi-borehole-constrained parameter inversion. After training, the EA-LSTM model served as a surrogate forward model representing the nonlinear mapping from the mining stage and boundary parameters to the pressure responses at the five extraction boreholes. During inversion, candidate combinations of the vertical stress correction coefficient, reservoir pressure, extraction pressure, and initial permeability were introduced into the trained model. The discrepancies between the predicted and measured pressures at the five boreholes were jointly minimized to identify the optimal parameter combination. Compared with inversion based on a single monitoring point, the use of five borehole-pressure constraints preserves the spatial variability among the monitoring locations and reduces the ambiguity of boundary-parameter identification. The optimal parameter combination was subsequently incorporated into the COMSOL forward model to reconstruct the three-dimensional CBM pressure field.

Model evaluation and visualization. Model performance was evaluated using the mean squared error (MSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and coefficient of determination (R^2). Lower values of MSE, MAE, and MAPE indicate smaller prediction errors, whereas an R^2 value closer to 1 indicates better agreement between the predicted and reference values. MSE and R^2 were adopted as the primary performance indicators. In addition, the PSO convergence history, training and validation learning curves, and comparisons between the predicted and reference borehole pressures were used to evaluate the optimization process, training stability, and predictive accuracy.

In summary, the proposed EA-LSTM framework differs from a conventional LSTM prediction workflow in four principal aspects: (1) mining-stage-aware organization of the numerical sample; (2) parallel temporal attention and residual-LSTM feature extraction; (3) joint inversion constrained by pressure measurements from five extraction boreholes; (4) closed-loop coupling with the COMSOL forward model. Consequently, the methodological contribution lies in the problem-specific adaptation and integration of these components for CBM pressure-field inversion under dynamic mining conditions.

After training, the optimal hyperparameters were determined as follows: 94 LSTM units in the first layer, 103 LSTM units in the second layer, a dropout rate of 0.156, a learning rate of 9.74×10^{-4} , an L2 regularization strength of 0.0011, and a batch size of 8.

3. Results

3.1. Model Training and Algorithm Comparison

The enhanced Attention-LSTM model was trained using the obtained dataset. The evolution of the MSE during the optimization process is shown in Figures 6 and 7. As the iteration process progressed, the MSE gradually decreased and converged to a stable value. In the later stages of training, the difference between the training and validation error remained within a narrow range, and no sign of overfitting characteristics—such as continuous reduction in training error accompanied by a significant increase in validation error—was observed.

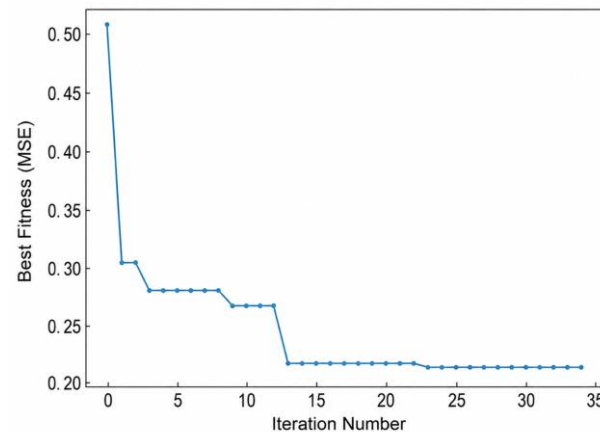


Figure 6. PSO convergence curve.

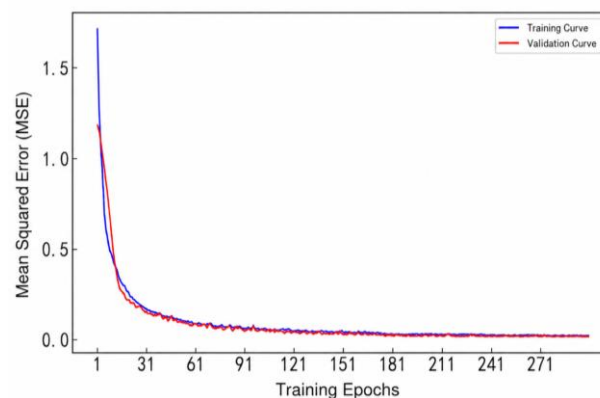


Figure 7. Learning curve.

This result demonstrates the effectiveness of the PSO algorithm in optimizing the hyperparameters of the LSTM model. Under the current sample-size conditions, the proposed framework, which integrates Dropout regularization, L2 weight regularization, early stopping, and PSO-based hyperparameter optimization, exhibits good generalization capability while maintaining high inversion accuracy, with no evident signs of overfitting. These results indicate that the model performs reliably within the defined parameter space and the available sample range.

Using the constructed dataset, ten algorithmic models were trained and validated for comparison: Random Forest (RF), Decision Tree (DT), Lasso Regression (LR), Extra Trees (ET), Temporal Convolutional Network (TCN), Bidirectional Long Short-Term Memory (BiLSTM), Transformer, Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM), and the proposed Enhanced Attention-LSTM (EA-LSTM) model.

Figure 8 and Table 4 compare the performance of the ten algorithmic models across four evaluation metrics: MAE, MSE, R^2 , and MAPE. The results show that the EA-LSTM model achieves the best overall performance, with MAE = 0.08%, MSE = 0.01%, MAPE = 1.79%, and R^2 = 0.99.

Table 4. Performance parameters of different algorithms.

Algorithm Model	MAE	MSE	R^2	MAPE
DT	0.34	0.22	0.80	5.2%
RF	0.29	0.17	0.85	3.5%
LR	0.22	0.07	0.91	5.5%
ET	0.16	0.05	0.95	2.2%
Transformer	0.73	0.79	0.24	18.4%
TCN	0.26	0.11	0.90	6.7%
BiLSTM	0.12	0.03	0.97	2.5%
GRU	0.12	0.03	0.97	2.5%
LSTM	0.13	0.03	0.97	2.2%
EA-LSTM	0.08	0.01	0.99	1.8%

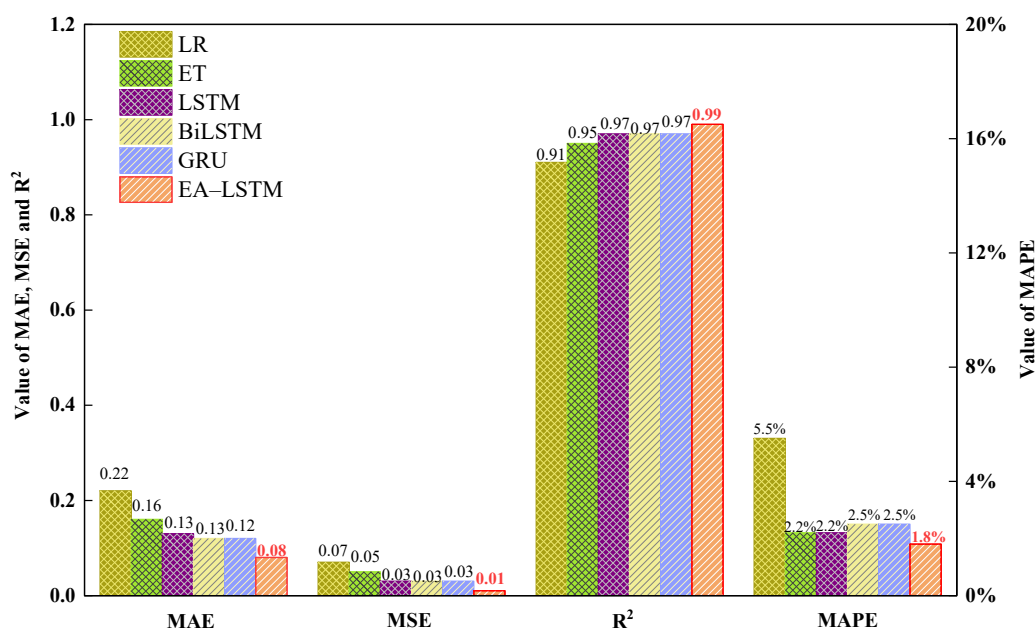


Figure 8. Algorithm comparison. Red labels identify the EA-LSTM results and the best results.

The Transformer achieved lower prediction accuracy than the recurrent neural network models for the present dataset. This result may be attributed to the short input-sequence length and the limited number of training samples. Because each input sequence contained only three consecutive working-face advancement stages, the Transformer's ability to capture long-range dependencies through the self-attention mechanism could not be fully exploited. In addition, its predictive performance was more sensitive to the network architecture and hyperparameter settings under the available sample-size conditions. In contrast, the EA-LSTM more effectively captured the short-range dependencies among adjacent mining stages and the nonlinear relationship between the boundary parameters and the borehole-pressure responses. Therefore, the EA-LSTM was selected as the surrogate model for the subsequent boundary-parameter inversion.

Figure 9 and Table 5 compare the predicted and measured pressure values for the five CBM production wells under the corresponding boundary conditions. The regression curve of the EA-LSTM model in Figure 9 closely follows the ideal fit, indicating that the

model effectively captures the complex nonlinear relationship between the boundary parameters and CBM production well pressures.

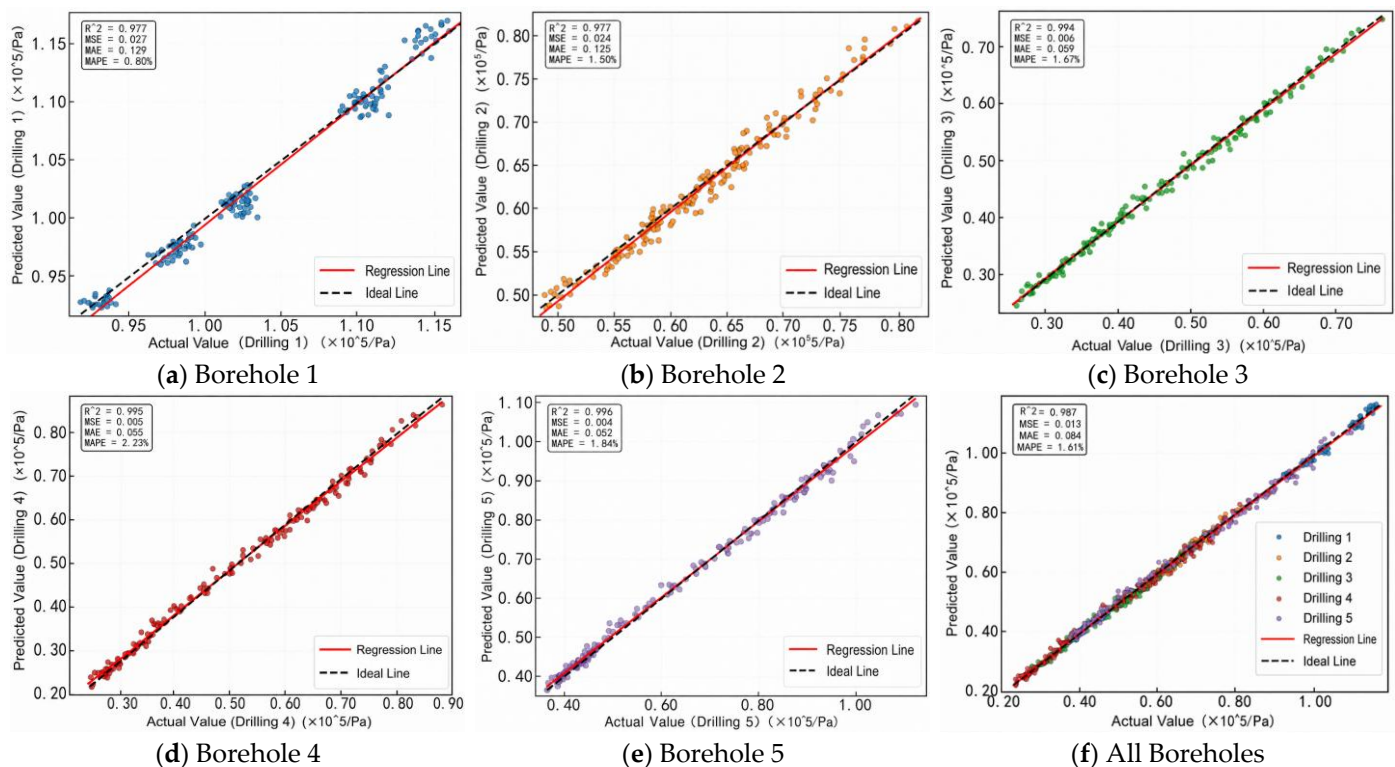


Figure 9. Regression scatter plots of borehole pressure inversion.

Table 5. Performance parameters of the EA-LSTM model.

EA—LSTM	Borehole 1	Borehole 2	Borehole 3	Borehole 4	Borehole 5
R ²	0.977	0.977	0.994	0.995	0.996
MSE	0.027	0.024	0.006	0.005	0.004
MAE	0.129	0.125	0.059	0.055	0.052
MAPE	0.80%	1.50%	1.67%	2.23%	1.84%

In terms of prediction accuracy, Well 5 exhibits the best performance, followed by Wells 3 and 4, whereas Wells 1 and 2 show slightly larger prediction errors. These differences are mainly attributable to local pressure-gradient variations, the spatial locations of the boreholes, and heterogeneity in the permeability of the surrounding rock. Overall, the model achieved an MSE of 0.013 and an R² of 0.987, demonstrating that the EA-LSTM model can accurately predict borehole-pressure responses within the training dataset.

3.2. Pressure Prediction and Field Reconstruction

Cases 1–3 in Table 6 represent three independent sets of borehole-pressure measurements obtained under different operating conditions. The measured borehole pressures were used as observational constraints for boundary-parameter inversion using the trained and validated EA-LSTM surrogate model. PSO was employed to identify the optimal boundary parameters of the COMSOL numerical model within the predefined feasible ranges. After iterative optimization, the optimal parameter combination for each case was obtained, as listed in Table 7. These inverted parameters were subsequently incorporated into the COMSOL model to perform forward simulations of the corresponding CBM pressure fields.

Table 6. Borehole pressure.

Case	Borehole 1 (kPa)	Borehole 2 (kPa)	Borehole 3 (kPa)	Borehole 4 (kPa)	Borehole 5 (kPa)
1	108.475	71.348	62.932	69.827	89.950
2	95.845	52.575	31.553	28.640	42.333
3	115.145	70.942	52.255	53.172	70.859

The simulated borehole pressures were compared with the corresponding field measurements, as summarized in Table 8. The field pressures were measured using pressure sensors with an accuracy of $\pm 0.5\%$ of full scale (FS), where FS denotes the full-scale measurement range. The relative errors between the simulated and measured borehole pressures ranged from 0.41% to 5.07%, indicating good overall agreement. These results demonstrate that the EA-LSTM model can effectively identify the boundary parameters and provide a reliable basis for reconstructing the CBM pressure field.

Table 7. Optimal combination of parameters.

Case	Correction Factor	Reservoir Pressure (MPa)	Drainage Pressure (kPa)	Initial Permeability (10^{-17} m^2)
1	0.89	1.38	29	9.77
2	0.84	0.45	22	1.03
3	0.68	1.15	33.32	10

Figure 10 presents the three-dimensional pressure-field distribution obtained using the optimal parameter combination. As expected, the gas flow migrates from high-pressure zones to low-pressure zones, converging around the production wells while maintaining a consistent overall flow pattern. These results provide a reliable numerical basis for subsequent pressure-field analysis and engineering evaluation.

By continuously incorporating the measured CBM production-well pressures at specific monitoring locations into the EA-LSTM model during the extraction process, and using the inverted boundary parameters as inputs to the COMSOL Multiphysics forward model, the CBM pressure field can be dynamically reconstructed, updated, and monitored throughout the extraction process.

Table 8. Comparison of actual and inverted borehole pressure values.

Case	Item	Borehole 1 (kPa)	Borehole 2 (kPa)	Borehole 3 (kPa)	Borehole 4 (kPa)	Borehole 5 (kPa)
1	Measured value	108.475	71.348	62.932	69.827	89.950
	Inverse value	107.721	71.644	62.353	68.954	90.546
	Absolute error	0.754	0.296	0.579	0.873	0.596
	Relative error	0.70%	0.41%	0.92%	1.25%	0.66%
2	Measured value	95.845	52.575	31.553	28.640	42.333
	Inverse value	93.524	53.657	30.825	28.899	42.732
	Absolute error	2.321	1.082	0.728	0.259	0.399
	Relative error	2.4%	2.06%	2.31%	0.90%	0.94%
3	Measured value	115.145	70.942	52.255	53.172	70.859
	Inverse value	116.210	71.397	54.645	55.870	73.560
	Absolute error	1.065	0.455	2.390	2.698	2.701
	Relative error	0.92%	0.64%	4.57%	5.07%	3.81%

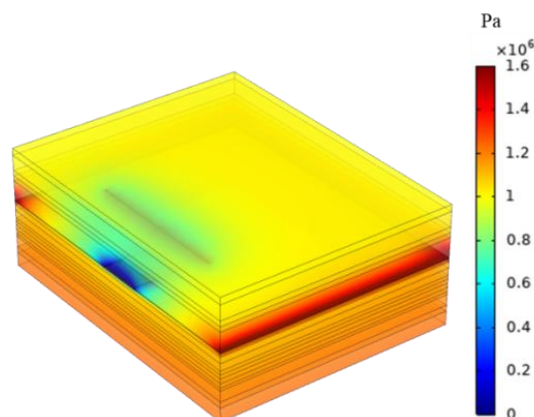


Figure 10. Three-dimensional numerical model of the coalbed methane pressure field at Xinjing Mine.

4. Discussion

During the gas extraction process, changes in pressure distribution directly affect both the CBM occurrence state and the mechanical response of the coal seam. When gas extraction is coupled with mining-face advancement, the spatial distribution of the CBM pressure field becomes difficult to visualize directly. In this study, a collaborative computational framework combining EA-LSTM parameter inversion with COMSOL Multiphysics numerical forward simulation was developed to reconstruct the pressure-field distribution under conditions of limited monitoring data.

Compared with conventional analytical approaches based on repeated numerical trial-and-error iterations, the proposed framework significantly reduces parameter exploration within the feasible parameter space, thereby improving the efficiency of pressure-field analysis. It should be noted that the intelligent model does not replace numerical simulation or field monitoring; rather, it acts as an inversion tool for the mechanistic model, while the final pressure-field distribution is still obtained through COMSOL forward calculations.

To ensure simulation reliability, the model was validated using field-measured borehole-pressure data from Coal Seam No. 3, reported in Reference [49] (Table 9). The comparison shows that the model error is less than 6%. In addition, the simulated stress conditions were compared with the field measurements reported for the Xinjing Mine in Reference [50] (Table 10), yielding relative errors ranging from 1.07% to 6.79%.

Table 9. Comparison of borehole pressure data.

Item	Borehole 1 (MPa)	Borehole 2 (MPa)	Borehole 3 (MPa)	Borehole 4 (MPa)
Measured Value	1.01	0.85	1.05	1.03
Simulated values	1.017	0.897	1.047	1.014
Absolute error	0.007	0.047	0.003	0.016
Relative error	0.6%	5.5%	0.28%	1.5%

In engineering applications, error margins below 10–15% are generally considered acceptable for evaluating model reliability and inversion accuracy. Previous studies on the inversion of surrounding-rock mechanical parameters have shown that when the maximum discrepancy between the forward-simulation results and the measured displacements is less than 15%, the inversion results can be regarded as sufficiently accurate [51]. The present validation demonstrates that the proposed model achieves an accuracy suitable for engineering applications.

Table 10. Comparison of vertical stress data.

Item	Point 1 (MPa)	Point 2 (MPa)	Point 3 (MPa)	Point 4 (MPa)
Actual Value	15.28	15.03	11.36	11.20
Simulated value	15.03	14.68	12.13	11.08
Absolute error	0.25	0.35	0.77	0.12
Relative error	1.64%	2.32%	6.79%	1.07%

The effectiveness of the proposed method mainly depends on establishing a reliable nonlinear mapping between the COMSOL Multiphysics boundary parameters and the locally measured borehole pressures. In this regard, the EA-LSTM model performed well, achieving a relative error range of 0.41–5.07%, which is smaller than the forward-simulation error. This demonstrates that the proposed intelligent algorithm can effectively complement conventional geostatistical approaches and trial-and-error parameter analysis.

- (1) Engineering application. The proposed method provides a practical framework for reconstructing and visualizing the three-dimensional CBM pressure field from sparse monitoring data. Using only a limited number of borehole-pressure measurements, which are readily available in the field at relatively low cost, the three-dimensional reservoir pressure field can be reconstructed through intelligent inversion. This approach provides a global view of the pressure distribution, extending well beyond the local monitoring locations. The relative errors obtained (0.41–5.07%) fall well within the acceptable range for engineering applications, confirming the practical reliability of the proposed method.
- (2) Computational efficiency. This proposed workflow establishes an integrated sequence of “measured data acquisition → intelligent inversion → numerical model updating”, substantially reducing the repetitive trial-and-error adjustment of boundary parameters required in conventional numerical simulations. Consequently, it provides an efficient framework for rapid pressure-field updating during working-face advancement.
- (3) Extraction-scheme optimization. Under given geological conditions and borehole layouts, the reconstructed pressure field can be used to analyze the inter-well pressure connectivity, identify residual high-pressure zones, and evaluate pressure-gradient distributions. These results provide valuable guidance for optimizing extraction parameters, adjusting borehole layouts, and assessing extraction performance.

The inversion results show that CBM production progressively reshapes the reservoir pressure field, creating pressure-gradient channel pathways that drive gas migration from peripheral high-pressure regions toward the low-pressure zones surrounding the production wells. When the production wells are located within the middle to lower portions of the fractured zone and the extraction pressure is appropriately controlled, a stable low-pressure convergence zone develops around the boreholes, promoting gas migration from the surrounding coal seam toward the production wells. This pressure distribution is consistent with the expected mechanisms of pressure depletion and gas convergence during CBM extraction.

Although the model performance was evaluated using an independent test set, all samples were generated from a single engineering case. Therefore, the transferability of the proposed framework to other mines and geological conditions requires further validation using multi-site numerical simulations and field-monitoring data. In addition, although layer-dependent material properties were assigned to represent the differences among lithological units, the mechanical and seepage properties within each layer were assumed to be homogeneous and isotropic. In actual coal seams, however, transverse isotropy associated with bedding and cleat systems may produce direction-dependent stress

redistribution and pressure propagation. Consequently, the present study does not quantify the uncertainty associated with anisotropic elasticity and permeability. Future work will incorporate anisotropic constitutive models and permeability tensors into the COMSOL forward model and compare the reconstructed pressure fields obtained under isotropic and transversely isotropic assumptions.

The present study does not attempt to establish a closed-form analytical or empirical relationship for direct engineering estimation. The borehole-pressure responses are jointly controlled by the working-face advancement distance, in situ stress state, reservoir pressure, extraction pressure, initial permeability, and borehole locations. Interactions among these variables may result in different parameter combinations producing similar local pressure responses, leading to non-unique solutions. Consequently, an empirical relationship derived solely from the current dataset would likely be site-specific and of limited applicability beyond the investigated parameter ranges. Future work will expand both the numerical and field datasets to include a wider range of geological and extraction conditions and will combine parameter-sensitivity analysis, response-surface modeling, and symbolic regression to derive and independently validate a simplified empirical relationship for rapid preliminary engineering estimation. Such a relationship would complement, rather than replace, the complete EA-LSTM-COMSOL framework for accurate boundary-parameter inversion and three-dimensional pressure-field reconstruction.

5. Conclusions

This study addresses the challenge of sparse pressure monitoring in CBM production wells, the difficulty in characterizing the global pressure field, and the low efficiency of traditional trial-and-error numerical simulations. To overcome these limitations, an intelligent pressure-field inversion framework coupling the Enhanced Attention-LSTM (EA-LSTM) model with the COMSOL Multiphysics mechanistic model was developed. Using Coal Seam No. 3 at Xinjing Mine as the engineering case study, a multi-parameter sample library was constructed to train the model, and the inverted parameters were then reloaded into the COMSOL model to reconstruct the pressure field. The main conclusions are as follows:

- (1) An EA-LSTM-COMSOL collaborative inversion framework was developed, in which the vertical stress correction coefficient, reservoir pressure, production pressure, and initial permeability were selected as the inversion parameters, while the working-face-advancement distance was introduced as an auxiliary operational variable. The pressures measured at five production boreholes were jointly used as inversion constraints. This framework enables rapid identification of the boundary parameters and reconstruction of the three-dimensional CBM pressure field under limited monitoring conditions, providing an effective approach for analyzing CBM extraction.
- (2) To address the difficulty of directly obtaining comprehensive CBM pressure-field data from field measurements and the limited availability of field monitoring data, the COMSOL numerical model was validated against field observations. The relative errors ranged from 0.6% to 5.5% for the borehole pressures and from 1.07% to 6.79% for the stress field values, demonstrating good agreement between the simulated and measured results. These errors satisfy the accuracy requirements for pressure-field trend analysis and inversion validation. After the optimal inverted parameters were incorporated into the COMSOL forward model, the relative errors between the calculated and measured borehole pressures ranged from 0.41% to 5.07%, with an average relative error of 1.84%.
- (3) Among the ten tested models, the EA-LSTM achieved the best predictive performance, with an overall MSE of 0.013 and R^2 of 0.987. Compared with DT, RF, LR, ET,

TCN, BiLSTM, GRU, LSTM, and Transformer, the proposed model showed lower prediction errors and better fitting accuracy. These results demonstrate that the EA-LSTM model effectively captures the nonlinear relationship between boundary parameters and borehole-pressure responses, making it well suited for pressure prediction and inversion under the investigated engineering conditions.

- (4) The reconstructed pressure field of Coal Seam No. 3 at the Xinjing Mine is generally consistent with the measured pressure distribution, indicating that the proposed inversion framework can reliably reproduce the spatial characteristics of the CBM pressure field. By integrating data-driven prediction with mechanism-based numerical constraints, the EA-LSTM-COMSOL framework improves the efficiency and reliability of boundary-parameter identification and pressure-field reconstruction under complex mining conditions.

Future work will expand both the numerical and investigate interpretable response-surface and symbolic-regression methods to derive and independently validate a simplified empirical relationship for rapid preliminary engineering estimation. Although the current model represents property contrasts among different lithological layers, fine-scale continuous or stochastic heterogeneity within individual layers was not explicitly considered because sufficiently dense, site-specific property data were unavailable. To address this limitation, high-resolution property fields generated using geostatistical methods or specialized geomodeling techniques will be integrated into the coupled COMSOL model to evaluate the influence of small-scale reservoir heterogeneity on the inversion results.

The applicability of the proposed framework will also be investigated for other subsurface reservoir-engineering problems characterized by sparse observations, uncertain boundary parameters, and coupled physical processes, including gas-condensate reservoirs, geothermal systems, shale hydrocarbon reservoirs, and other unconventional reservoirs. Such applications will require reservoir-specific reformulation of the governing equations, inversion parameters, monitoring variables, and training datasets to account for the corresponding multiphase flow, heat transfer, and geomechanical processes.

Author Contributions: Z.Z.: Writing—original draft, Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization. W.L.: Writing—review and editing, Methodology, Funding acquisition, Resources, Supervision, Conceptualization, Formal analysis, Project administration. F.G.: Writing—review and editing, Methodology, Investigation, Formal analysis, Software, Visualization. J.Y.: Writing—review and editing, Conceptualization, Visualization. All authors have read and agreed to the published version of the manuscript.

Funding: This work has been supported by the National Natural Science Foundation (U22A20167) awarded to Weiguo Liang.

Data Availability Statement: The data can be obtained from the corresponding author according to reasonable requirements. The data are not publicly available due to privacy.

Acknowledgments: The first author thanked other authors for their research contributions, and thanked the editors and reviewers for their kindness and valuable opinions.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

BiLSTM	Bidirectional Long Short-Term Memory
CBM	Coalbed Methane
DT	Decision Tree
ET	Extremely Randomized Trees

GRU	(Extra Trees)
LSTM	Gated Recurrent Unit
PSO	Long Short-Term Memory
MAE	Particle Swarm Optimization
MSE	Mean Absolute Error
BN	Mean Squared Error
DOF	Batch Normalization
EA-LSTM	Degree of Freedom
FS	Enhanced Attention-Based Long Short-Term Memory
LR	Full Scale
TCN	Lasso Regression
RF	Temporal Convolutional Network
MAPE	Random Forest
R ²	Mean Absolute Percentage Error
	Coefficient of Determination

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