

## Article

# Deformation Prediction Model for Soft Rock Tunnels Based on NWOA-LSTM Model

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## Abstract

Surrounding rock deformation in soft rock tunnels is controlled by complex nonlinear interactions among geological conditions, construction parameters, and support measures, making accurate prediction challenging. In this study, a project-scale deformation prediction dataset was constructed using field monitoring data from a sandy shale tunnel project. Eight engineering factors were selected as input variables, including excavation method, initial support strength, closure time, tunnel burial depth, lithology, rock integrity, groundwater condition, and the relative orientation between major structural planes and the tunnel. A hybrid prediction framework integrating a novel whale optimization algorithm (NWOA) and a long short-term memory (LSTM) network was developed. The proposed NWOA improves the standard whale optimization algorithm by introducing a nonlinear convergence strategy, an adaptive weight coefficient, and a dynamic spiral position updating mechanism to enhance the hyperparameter search process of the LSTM model. Model performance and stability were further assessed using repeated and nested cross-validation. The corresponding RMSEs were  $0.2294 \pm 0.0734$  and  $0.2219 \pm 0.0751$  percentage points, the MAEs were  $0.1427 \pm 0.0350$  and  $0.1505 \pm 0.0585$  percentage points, and the  $R^2$  values were  $0.8660 \pm 0.0548$  and  $0.8732 \pm 0.0599$ , respectively. These comparable results support project-specific predictive performance for the investigated tunnel sections.

**Keywords:** soft rock tunnel; tunnel deformation prediction; novel whale optimization algorithm; long short-term memory; deep learning



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## 1. Introduction

With the continuous expansion of transportation infrastructure into mountainous and geologically complex areas, tunnel construction under complex geological conditions has become increasingly common [1–3]. Soft rock tunnels are particularly prone to large deformation because soft rock masses usually exhibit low strength, weak cementation, strong weathering, and high sensitivity to excavation disturbance [4,5]. During tunnel excavation, stress redistribution, support–rock interaction, groundwater disturbance, and time-dependent deformation may jointly lead to excessive convergence, support cracking, and instability of the tunnel structure. Recent studies on subsea tunnel sealing and fractured porous media have also shown that groundwater chemistry, flow velocity, flow paths, and wettability can influence the engineering response of fractured rock [6,7]. Therefore,

accurate prediction of surrounding rock deformation is important for construction safety, support optimization, and risk control in soft rock tunnel engineering.

Traditional tunnel deformation analysis mainly relies on empirical assessment, theoretical calculation, and numerical simulation. These methods provide useful tools for understanding excavation-induced deformation, stress redistribution, and rock-mass failure mechanisms [8–12]. However, the deformation of soft rock tunnels is controlled by multiple coupled factors, including lithology, rock integrity, groundwater condition, tunnel burial depth, excavation method, and support measures. In practical engineering, the mechanical parameters and boundary conditions required for numerical models are often difficult to determine accurately because of geological heterogeneity and construction disturbance. As a result, field-monitoring-data-driven methods have attracted increasing attention for tunnel deformation prediction.

Machine learning methods have been increasingly applied in underground engineering because of their ability to capture nonlinear relationships between engineering parameters and target responses. Models such as support vector machines, backpropagation neural networks, and their optimized variants have been used for rockburst classification, tunnel squeezing prediction, rock strength prediction, surrounding rock parameter inversion, and surrounding rock grade prediction [13–17]. More recently, deep learning models have also been introduced into tunnel and geotechnical prediction tasks. For example, hybrid deep learning models have been used for rock tunnel deformation prediction, and LSTM-based models have been applied to tunnel boring machine performance and geotechnical bearing-capacity prediction [18–20]. Although LSTM networks were originally developed for sequential and time-dependent data, their gated structure can also be used to establish nonlinear mappings between engineering parameters and prediction outputs when the input is organized as a single-step sequence. The prediction performance of LSTM models is strongly affected by hyperparameters, such as the number of hidden neurons, learning rate, regularization coefficient, and dropout rate [21,22]. Manual selection of these parameters is time-consuming and depends heavily on prior experience. Metaheuristic optimization algorithms provide an effective way to search for suitable neural-network hyperparameters [23]. Among them, the whale optimization algorithm (WOA), proposed by Mirjalili and Lewis [24], has been widely used because of its simple structure and few control parameters. WOA-based hybrid models have also been applied in tunnel engineering and other engineering optimization problems [25,26]. However, the standard WOA adopts a linear convergence factor and a fixed spiral updating strategy, which may limit the balance between global exploration and local exploitation during parameter optimization. When WOA is used for LSTM hyperparameter search, this limitation may affect the stability and accuracy of the final prediction model.

To address these issues, this study proposes an NWOA-LSTM prediction framework for soft rock tunnel deformation. The proposed method improves the whale optimization process used for LSTM hyperparameter search by introducing a nonlinear convergence strategy, an adaptive weight coefficient, and a dynamic spiral position updating mechanism. These strategies are designed to enhance search diversity and optimization stability when determining key LSTM hyperparameters. The proposed framework is developed and tested using field monitoring data from a sandy shale tunnel project, in which eight geological and construction-related engineering factors are used as model inputs. In addition, the input structure of the LSTM model is clarified as a single-step sequence for tunnel-section-based prediction. The evaluation framework combines a fixed engineering case analysis with repeated stratified five-fold cross-validation and nested stratified cross-validation. Benchmark comparison, ablation analysis, residual analysis, and engineering interpretation

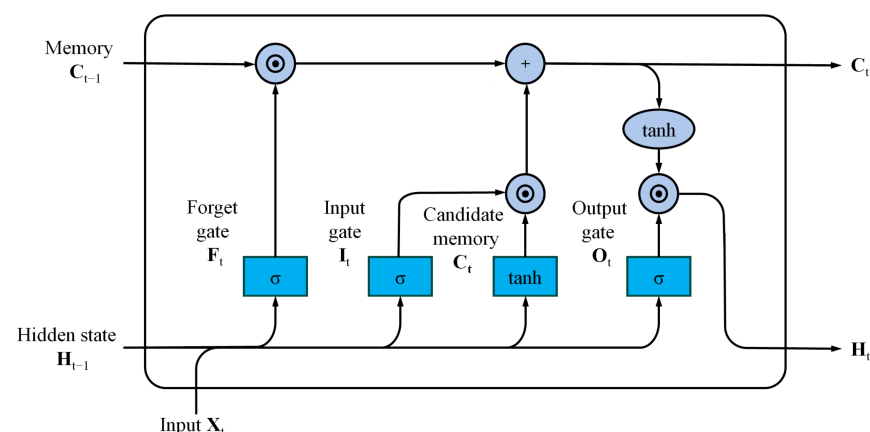
were also conducted to evaluate the prediction performance and practical applicability of the proposed model.

## 2. Methodology

### 2.1. LSTM Neural Network

The deformation of soft rock tunnels is governed by nonlinear interactions among geological conditions and construction parameters. In this study, each tunnel section was treated as an independent prediction sample and was represented by eight engineering variables: excavation method, initial support strength, closure time, tunnel burial depth, lithology, rock integrity, groundwater condition, and structural-plane orientation. The input vector of each section was reshaped as a  $1 \times 8$  tensor before being supplied to the LSTM network. Accordingly, both the time step and sequence length were set to 1.

As shown in Figure 1, a standard LSTM unit contains a candidate-cell transformation and three gating mechanisms. For the single-step input used in this study, the engineering variables are transformed into a candidate-cell representation and modulated by the input and output gates before the regression output is generated. These input-dependent multiplicative operations establish a gated nonlinear mapping between the engineering parameters and tunnel deformation. This structure enables the model to represent the coupled effects of geological conditions and construction parameters within each tunnel section. The LSTM was therefore adopted as the basic gated regression network, while NWOA was used to optimize the number of hidden units, learning rate, regularization coefficient, and dropout rate.



**Figure 1.** LSTM neural network unit structure.

With a sequence length of one, the present LSTM configuration models nonlinear interactions among the engineering variables within each tunnel section.

The LSTM cell operations are defined in Equations (1)–(6).

$$f_t = \sigma(W_f h_{t-1} + U_f x_t + b_f) \quad (1)$$

$$i_t = \sigma(W_i h_{t-1} + U_i x_t + b_i) \quad (2)$$

$$\bar{C}_t = \text{Tanh}(W_c h_{t-1} + U_c x_t + b_c) \quad (3)$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \bar{C}_t \quad (4)$$

$$O_t = \sigma(W_o h_{t-1} + U_o x_t + b_o) \quad (5)$$

$$h_t = O_t \cdot \text{Tanh}(C_t) \quad (6)$$

where  $f_t$ ,  $i_t$ , and  $O_t$  denote the forget, input, and output gates, respectively;  $\sigma$  and  $\tanh$  denote the sigmoid and hyperbolic-tangent activation functions, respectively;  $x_t$  is the input vector at time step  $t$ ;  $C_{t-1}$  and  $h_{t-1}$  are the previous cell state and hidden state, respectively;  $\bar{C}_t$ ,  $C_t$  and  $h_t$  are the candidate cell state, updated cell state, and hidden state at time step  $t$ , respectively;  $W_f$ ,  $W_i$ ,  $W_c$ , and  $W_o$  are the weight matrices associated with the previous hidden state;  $U_f$ ,  $U_i$ ,  $U_c$ , and  $U_o$  are the weight matrices associated with the current input; and  $b_f$ ,  $b_i$ ,  $b_c$ , and  $b_o$  are the corresponding bias vectors.

During model training and hyperparameter optimization, the mean squared error (MSE) was used as the loss and fitness function. The prediction performance of the final model was evaluated using the root mean squared error (RMSE), mean absolute error (MAE), and coefficient of determination ( $R^2$ ). These indices are defined as follows.

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (7)$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (8)$$

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (9)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (10)$$

where  $y_i$  is the measured deformation value,  $\hat{y}_i$  is the predicted deformation value, and  $n$  is the number of samples used for evaluation.

During hyperparameter optimization, the fitness MSE was calculated using the normalized target values. For prediction-performance evaluation, all outputs were inverse-transformed to the original deformation-rate scale before RMSE and MAE were calculated.

## 2.2. NWOA

WOA is a metaheuristic optimization method inspired by the hunting behavior of humpback whales. It is well-suited for solving global optimization problems in continuous spaces, featuring a small number of parameters, fast convergence speed, and straightforward implementation. These advantages have led to its widespread application in areas such as engineering optimization, machine learning parameter adjustment, and path planning. The algorithm operates through prey encirclement, bubble-net attack, and prey searching.

### (1) Prey encirclement

During the predation phase, the approximate optimal solution or top candidate solution within the current population is treated as the target prey. All other whale individuals then update their positions and converge toward this prey, guided by the location of the approximate optimal solution. This process can be mathematically described by Equations (11)–(15).

$$D = |C \cdot X^*(t) - X(t)| \quad (11)$$

$$X(t+1) = X^*(t) - A \cdot D \quad (12)$$

where  $D$  denotes the distance vector between the current search agent and the best solution found so far;  $X(t)$  and  $X(t+1)$  denote the positions of the search agent at iterations  $t$  and  $t+1$ , respectively;  $X^*(t)$  denotes the best position found up to iteration  $t$ ; and  $A$  and  $C$  are coefficient vectors defined in Equations (13) and (14), respectively.

$$A = 2a \cdot r_1 - a \quad (13)$$

$$C = 2 \cdot r_2 \quad (14)$$

$$a = 2 - \frac{2t}{T_{\max}} \quad (15)$$

where  $a$  is the convergence factor;  $r_1$  and  $r_2$  are random numbers on  $[0, 1]$ ; and  $T_{\max}$  is the maximum number of iterations.

#### (2) Bubble-net attack

The bubble-net attack phase consists of spiral position update and shrinking enclosure. The spiral position update process is mathematically described by Equations (16) and (17).

$$X(t+1) = D' \cdot e^{bl} \cdot \cos(2\pi l) + X^*(t) \quad (16)$$

$$D' = |X^*(t) - X(t)| \quad (17)$$

where  $D'$  represents the distance between the individual whale and its prey;  $b$  denotes the spiral shape parameter; and  $l$  is a random number within the range of  $[-1, 1]$ .

To simulate both the spiraling and encircling behaviors of whales simultaneously, each component of coefficient vector  $A$  is converted to its absolute value. When the absolute value of  $A$  is less than or equal to 1, the whale optimization algorithm assigns a 50% probability to both spiral position update and shrinking enclosure. A probability value  $p$  of 0.5 or higher triggers spiral position update. Otherwise, shrinking enclosure is implemented. This mechanism is mathematically described by Equation (18).

$$X(t+1) = \begin{cases} X^*(t) - A \cdot D, & P < 0.5 \\ D' \cdot e^{bl} \cdot \cos(2\pi l) + X^*(t), & P \geq 0.5 \end{cases} \quad (18)$$

#### (3) Prey searching

When the absolute value of coefficient vector  $A$  exceeds 1, the algorithm abandons position updates based on the optimal solution. Instead, it randomly selects an individual from the current population to guide the position update process. This random selection mechanism is mathematically defined by Equations (19) and (20).

$$X(t+1) = X_{rand} - A \cdot D \quad (19)$$

$$D = |C \cdot X_{rand}(t) - X(t)| \quad (20)$$

where  $X_{rand}$  represents the position of an individual randomly selected from the population.

#### (4) NWOA

Parameter  $a$  influences the balance between global exploration and local exploitation in the whale optimization algorithm. In the standard WOA, the convergence factor decreases linearly during the iteration process. In this study, a nonlinear convergence factor is introduced to adjust the search process more smoothly, as shown in Equation (21).

$$a = 2 - \left( \frac{t}{T_{\max}} \right)^2 \quad (21)$$

where  $t$  is the current iteration number and  $T_{\max}$  is the maximum number of iterations. Compared with the linear convergence factor in the standard WOA, the nonlinear convergence factor decreases gradually during the iteration process, which helps maintain search diversity during hyperparameter optimization.

The improved convergence factor adopts a larger value in the early stage of the process. This facilitates extensive exploration of the search space by the algorithm, boosting the likelihood of locating the global optimum and preventing entrapment in local optimal solutions. In the later stage, the factor shifts to a smaller value, enabling the algorithm to

perform precise searches around the optimal solution and thus enhancing the accuracy of the final result.

In addition, an adaptive weight coefficient is introduced into the position update process to improve the stability of the search. The adaptive weight coefficient is defined in Equation (22):

$$\omega = 0.45 \left[ 2 - \left( \frac{t}{T_{\max}} \right)^2 \right] \quad (22)$$

where  $\omega$  is the adaptive weight coefficient. The value of  $\omega$  decreases gradually with the iteration process, which adjusts the influence of the guiding position during the search and improves the stability of position updating.

After incorporating the adaptive weight coefficient, the position update equations are modified as Equations (23)–(25).

$$X(t+1) = \omega \cdot X^*(t) - A \cdot D \quad (23)$$

$$X(t+1) = \begin{cases} \omega X^*(t) - A \cdot D, & P < 0.5 \\ D' \cdot e^{bl} \cdot \cos(2\pi l) + \omega \cdot X^*(t), & P \geq 0.5 \end{cases} \quad (24)$$

$$X(t+1) = \omega \cdot X_{rand} - A \cdot D \quad (25)$$

The spiral shape parameter  $b$  is also typically set as a constant, leading to a single optimization approach during the process that hinders global search performance. To mitigate this limitation, this study employs a dynamic spiral update strategy, with the specific formulation provided in Equation (26).

$$b = e^{\cos\left(\frac{\pi t}{T_{\max}}\right)} \quad (26)$$

The improved dynamic spiral shape parameters introduce diverse optimization approaches, which in turn facilitate the identification of the optimal hyperparameter combination for the LSTM neural network.

### 2.3. NWOA-LSTM Prediction Framework

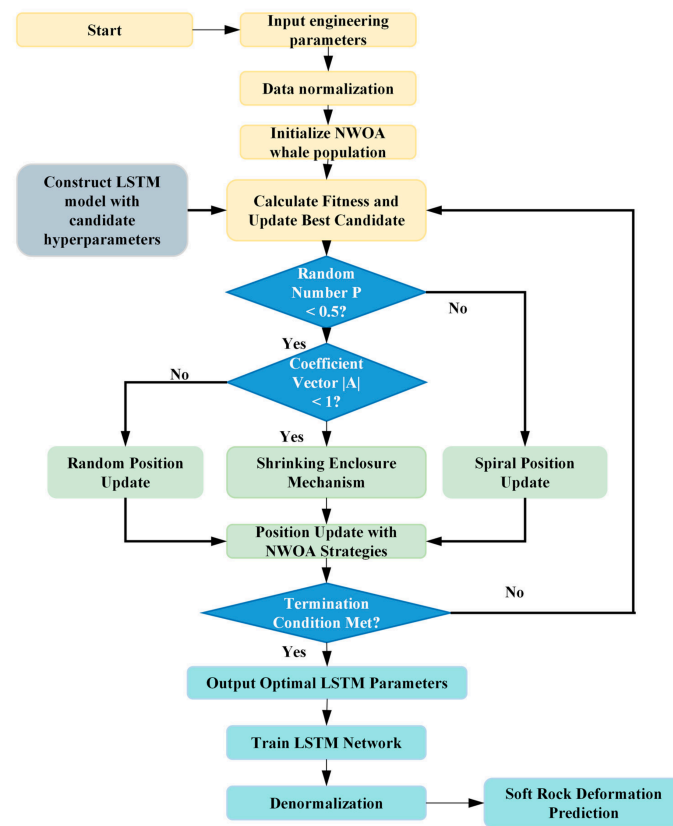
The NWOA-LSTM framework integrates data preprocessing, hyperparameter optimization, model fitting, and tunnel deformation prediction. As described in Section 2.1, each tunnel section was represented as a single-step sequence containing eight engineering variables, with a sequence length of 1 and an input dimension of 8. The model inputs and target values were transformed using min–max normalization:

$$x^* = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (27)$$

where  $x$  is the original value and  $x^*$  is the normalized value. In this study,  $x_{\min}$  and  $x_{\max}$  denote the minimum and maximum values of the corresponding variable calculated from the training dataset, respectively. The same normalization parameters were then used to transform the testing dataset.

During hyperparameter optimization, each whale position represented a candidate combination of the number of hidden units, learning rate, L2 regularization coefficient, and dropout rate. An LSTM model was constructed for each candidate, and its internal-validation MSE was used as the fitness value. The whale positions were iteratively updated using the nonlinear convergence factor, adaptive weight coefficient, and dynamic spiral updating mechanism. The same search ranges, computational budget, and stopping criterion were used for WOA-LSTM and all NWOA-LSTM variants. After the maximum

number of iterations was reached, the selected hyperparameters were used to refit the final LSTM model. The complete prediction workflow is illustrated in Figure 2.



**Figure 2.** Prediction framework of NWOA-LSTM for soft rock tunnel deformation.

Table 1 summarizes the hyperparameter search space, NWOA configuration, LSTM training settings, computational budget, and selected hyperparameter values.

**Table 1.** Hyperparameter optimization and training settings of the NWOA-LSTM model.

| Setting                       | Final Value |
|-------------------------------|-------------|
| Number of LSTM hidden units   | 96          |
| Learning rate                 | 0.008       |
| L2 regularization coefficient | 0.0004126   |
| Dropout rate                  | 0.30        |
| NWOA population size          | 4           |
| Maximum NWOA iterations       | 50          |
| Fitness function              | MSE         |
| Candidate-model evaluations   | 200         |
| Candidate-model epochs        | 12          |
| Candidate-model batch size    | 16          |
| Number of LSTM layers         | 1           |
| Post-LSTM dense layer         | 32 neurons  |
| Optimizer                     | Adam        |
| Final-model epochs            | 260         |
| Final-model batch size        | 8           |
| Early-stopping patience       | 50 epochs   |
| Random seed                   | 42          |
| Final trainable parameters    | 43,457      |

#### 2.4. Data Division and Validation Strategy

The study adopted a complementary validation framework comprising a fixed engineering case analysis, repeated stratified five-fold cross-validation, nested cross-validation, and repeated-partition model comparison. The database included 90 development sec-

tions and six predefined engineering case-validation sections. The six cases spanned the observed deformation range: Cases 1–3 represented low-deformation conditions, Case 4 represented a transitional deformation level, and Cases 5–6 represented relatively high-deformation conditions. This fixed case set was used to evaluate prediction agreement across different deformation magnitudes and to compare the case-level performance of the investigated models.

For the fixed case analysis, the 90 development sections were divided into a model-training subset and an internal validation subset at a ratio of 80:20, with the random seed set to 42. Candidate hyperparameter combinations were evaluated using the internal validation MSE. After hyperparameter selection, the final model was refitted using all 90 development sections and subsequently evaluated on the six fixed case-validation sections. The preprocessing parameters were estimated from the development data and then applied to the fixed case set. All models used the same development data, case set, preprocessing procedure, and evaluation metrics.

Generalization performance was evaluated using two repetitions of stratified five-fold cross-validation on the 90 development sections. Stratification was performed according to three deformation-rate intervals:  $\leq 0.5\%$ ,  $>0.5\text{--}1.0\%$ , and  $>1.0\%$ . Hyperparameter selection and preprocessing were conducted exclusively within each outer training fold. Every development section appeared in an outer test fold exactly twice, producing ten outer-fold estimates. Performance was summarized using the mean and standard deviation of RMSE, MAE, and  $R^2$  after inverse transformation to the original deformation-rate scale.

A five-by-three nested stratified cross-validation procedure was further conducted. The outer loop comprised five stratified folds, while three-fold cross-validation within each outer training fold was used to evaluate the candidate NWOA hyperparameters. The selected model was refitted using the complete outer training fold and evaluated on the corresponding outer test fold. In addition, ten stratified 80:20 repeated partitions were used for model comparison and ablation analysis.

### 3. Engineering Background and Sample Database Construction

#### 3.1. Engineering Overview of the Soft Rock Tunnel Project

This study was conducted using data from a specific tunnel project, focusing on 13 asymmetrically loaded sandy shale tunnels within the project scope. The total length of the tunnel group in the research area is 22,237 m, situated in terrain with undulations and a maximum burial depth of approximately 439 m. The natural transverse slope ranges from  $18^\circ$  to  $40^\circ$ , with local steep sections. The regional geological structure is relatively complex, featuring the Tianjiagou reverse fault and Kongjiafan fault. Influenced by these geological structures, joint fissures are well-developed, rock layers are severely compressed, and the surrounding rock of the tunnels exhibits poor self-stability. The tunnel distribution area is covered by Quaternary Holocene artificial accumulation gravel soil, Quaternary slope angular gravel soil, and slope residual silty clay, with sandy shale as the underlying bedrock.

The tunnels were excavated using step-based methods, including the full-face method, double-step method, three-step method, and three-step seven-bench reserved core soil method. Composite lining was adopted, with full-ring I-beams or H-steel arches. During construction, some tunnel sections passed through highly weathered, thin-bedded sandy shale with well-developed joints, large dip angles, and very poor rock mass cementation. These sections are also heavily affected by geological structures, with prominent fold development, resulting in extremely low overall strength of the surrounding rock at the excavation face. Severe localized deformation occurred during construction, extending from the upper part of the left tunnel wall to the left arch waist, leading to asymmetric

tunnel deformation. The maximum deformation reached 85 cm, causing serious issues such as cracking and sliding of the initial support.

### 3.2. Data Preprocessing of Soft Rock Tunnels

For the asymmetrically loaded sandy shale tunnel sections investigated in this study, conventional monitoring indicators, such as crown settlement and convergence, do not fully characterize the overall and localized deformation patterns. Therefore, complete cross-sectional deformation data were obtained by comparing tunnel-section scans acquired before and after the installation of the initial support, with the initial-support thickness excluded from the calculation.

The basic deformation level is determined by the mean relative deformation ( $\bar{\varepsilon}$ ) of the tunnel, as shown in Equations (28) and (29).

$$\bar{\varepsilon} = \frac{\sum_{i=1}^m \bar{q}_i l_i}{LR} \quad (28)$$

$$\bar{q}_i = \frac{1}{l_i} \int_0^{l_i} q_i(l) dl \quad (29)$$

where  $\bar{\varepsilon}$  denotes the mean relative deformation of the tunnel section;  $\bar{q}_i$  is the mean deformation along monitoring segment  $i$ ;  $q_i(l)$  denotes the local deformation at circumferential coordinate  $l$  along segment  $i$ ;  $l_i$  is the circumferential length of segment  $i$ ;  $m$  is the total number of monitored segments ( $m = 5$  in this study);  $L$  is the total monitored circumferential length of the tunnel section, excluding the invert; and  $R$  is the tunnel-span radius.

The results of deformation measurements for the 90 monitored soft rock tunnel sections is shown in Table 2.

**Table 2.** Deformation measurements for the 90 monitored soft rock tunnel sections.

| No. | $\bar{q}_1$ | $l_1$ | $\bar{q}_2$ | $l_2$ | $\bar{q}_3$ | $l_3$ | $\bar{q}_4$ | $l_4$ | $\bar{q}_5$ | $l_5$ | $\bar{\varepsilon}$ |
|-----|-------------|-------|-------------|-------|-------------|-------|-------------|-------|-------------|-------|---------------------|
| 1   | 10.4        | 4.98  | 17.7        | 5.5   | 10.8        | 3.57  | 2.4         | 5.42  | 3.9         | 6.97  | 0.13%               |
| 2   | 11.6        | 5.42  | 19.7        | 6.19  | 11.8        | 3.6   | 2.1         | 5.67  | 3.6         | 6.97  | 0.15%               |
| 3   | 11.7        | 5.48  | 19.9        | 6.07  | 11.9        | 3.6   | 2.1         | 5.61  | 3.7         | 7.09  | 0.15%               |
| 4   | 10.2        | 5.14  | 18          | 5.27  | 11.9        | 3.69  | 2.9         | 5.43  | 4.8         | 7.12  | 0.14%               |
| 5   | 10.6        | 5.64  | 19.1        | 5.86  | 12.8        | 3.78  | 2.9         | 5.69  | 5           | 7.16  | 0.15%               |
| 6   | 10.1        | 5.31  | 18.4        | 5.04  | 13          | 3.81  | 3.5         | 5.44  | 5.8         | 7.28  | 0.15%               |
| 7   | 10          | 5.44  | 18.4        | 5.18  | 13          | 3.82  | 3.4         | 5.48  | 5.7         | 7.3   | 0.15%               |
| 8   | 10.1        | 5.66  | 18.5        | 5.92  | 13.1        | 3.85  | 3.2         | 5.78  | 5.5         | 7.07  | 0.13%               |
| 9   | 9.5         | 5.79  | 18.2        | 5.65  | 13.7        | 3.96  | 3.7         | 5.76  | 6.3         | 7.23  | 0.13%               |
| 10  | 8.1         | 5.64  | 16.6        | 6.16  | 13.8        | 4.1   | 4.1         | 6.15  | 7.1         | 6.67  | 0.13%               |
| 11  | 9.8         | 5.73  | 18.8        | 5.09  | 14.1        | 3.96  | 3.9         | 5.54  | 6.7         | 7.49  | 0.14%               |
| 12  | 8.1         | 6.15  | 16.9        | 5.14  | 14.3        | 4.1   | 4.3         | 5.65  | 7.5         | 7.7   | 0.13%               |
| 13  | 8.5         | 5.9   | 17.3        | 5.65  | 14.3        | 4.1   | 4.2         | 5.9   | 7.3         | 7.18  | 0.14%               |
| 14  | 8.9         | 5.92  | 17.9        | 5.38  | 14.4        | 4.06  | 4.2         | 5.74  | 7.2         | 7.39  | 0.14%               |
| 15  | 9.4         | 5.94  | 18.4        | 5.12  | 14.5        | 4.03  | 4.1         | 5.59  | 7.1         | 7.59  | 0.14%               |
| 16  | 8.9         | 6.15  | 18          | 5.14  | 14.8        | 4.1   | 4.3         | 5.65  | 7.5         | 7.7   | 0.14%               |
| 17  | 11.1        | 6.15  | 21.4        | 5.14  | 16.2        | 4.1   | 4.3         | 5.65  | 7.5         | 7.7   | 0.16%               |
| 18  | 12.7        | 4.74  | 8.4         | 7.83  | 16.3        | 4.44  | 6.8         | 5.48  | 1.3         | 8.55  | 0.10%               |
| 19  | 13.8        | 5.15  | 9.1         | 7.5   | 17          | 4.64  | 7.4         | 5.67  | 1.5         | 8.01  | 0.12%               |
| 20  | 27.1        | 5.2   | 40.8        | 6.23  | 17.4        | 3.11  | 0.2         | 5.2   | 0.2         | 7.26  | 0.22%               |
| 21  | 1           | 6.08  | 10.5        | 6.08  | 18          | 5.08  | 8.1         | 7.09  | 14.2        | 6.08  | 0.14%               |
| 22  | 14.1        | 6.15  | 25.9        | 5.14  | 18.2        | 4.1   | 4.4         | 5.65  | 7.6         | 7.7   | 0.18%               |
| 23  | 20.9        | 5.68  | 38.5        | 5.69  | 18.7        | 3.61  | 0.2         | 5.42  | 0.2         | 7.48  | 0.23%               |
| 24  | 1.1         | 7.1   | 11          | 4.05  | 18.9        | 5.09  | 8.5         | 6.09  | 14.9        | 8.13  | 0.14%               |
| 25  | 14.7        | 6.15  | 36.1        | 5.14  | 19.9        | 4.1   | 0.2         | 5.65  | 0.2         | 7.7   | 0.20%               |
| 26  | 17.3        | 5.02  | 12.7        | 7.6   | 20          | 4.58  | 8           | 5.61  | 1.9         | 8.17  | 0.14%               |
| 27  | 1.7         | 7.1   | 21.2        | 4.05  | 20.7        | 5.09  | 4.4         | 6.09  | 7.6         | 8.13  | 0.15%               |
| 28  | 22.1        | 7.1   | 41          | 4.05  | 21.5        | 5.09  | 0.2         | 6.09  | 0.2         | 8.13  | 0.18%               |
| 29  | 2.3         | 7.1   | 31.4        | 4.05  | 22.4        | 5.09  | 0.2         | 6.09  | 0.2         | 8.13  | 0.11%               |
| 30  | 20.9        | 4.9   | 16.4        | 7.7   | 23.3        | 4.52  | 8.6         | 5.55  | 2.4         | 8.34  | 0.17%               |

Table 2. Cont.

| No. | $\bar{q}_1$ | $l_1$ | $\bar{q}_2$ | $l_2$ | $\bar{q}_3$ | $l_3$ | $\bar{q}_4$ | $l_4$ | $\bar{q}_5$ | $l_5$ | $\bar{\varepsilon}$ |
|-----|-------------|-------|-------------|-------|-------------|-------|-------------|-------|-------------|-------|---------------------|
| 31  | 2.4         | 5.2   | 33          | 6.23  | 23.5        | 3.11  | 0.2         | 5.2   | 0.2         | 7.26  | 0.17%               |
| 32  | 7.6         | 5.68  | 29.2        | 5.69  | 24.1        | 3.61  | 2.3         | 7.49  | 3.9         | 7.48  | 0.18%               |
| 33  | 17.1        | 12.96 | 41.1        | 5.34  | 24.2        | 2.66  | 0.2         | 2.63  | 6.8         | 3.69  | 0.26%               |
| 34  | 3.2         | 6.37  | 28.7        | 5.1   | 24.2        | 4.59  | 2.2         | 7.15  | 3.7         | 7.4   | 0.16%               |
| 35  | 6.6         | 6.39  | 35.1        | 4.87  | 24.7        | 4.35  | 0.2         | 6.79  | 0.2         | 7.8   | 0.17%               |
| 36  | 13.6        | 6.17  | 34.7        | 5.22  | 30.1        | 4.25  | 6.2         | 7.13  | 1.4         | 7.51  | 0.20%               |
| 37  | 8.2         | 5.5   | 34.3        | 5.89  | 30.1        | 3.42  | 2.4         | 7.15  | 7.2         | 7.4   | 0.20%               |
| 38  | 8.9         | 5.44  | 40.1        | 5.96  | 30.4        | 3.36  | 0.2         | 8.42  | 0.3         | 7.37  | 0.18%               |
| 39  | 27.9        | 4.64  | 23.6        | 7.91  | 31.5        | 4.39  | 9.8         | 5.44  | 3.2         | 8.67  | 0.23%               |
| 40  | 10.3        | 5.69  | 38          | 5.73  | 32          | 3.68  | 3.2         | 8.24  | 0.9         | 7.38  | 0.19%               |
| 41  | 18.4        | 6.23  | 44.3        | 6.23  | 32.3        | 6.23  | 3.9         | 6.23  | 10.2        | 6.23  | 0.28%               |
| 42  | 12.9        | 5.21  | 43.4        | 7.28  | 33.6        | 5.21  | 2.6         | 8.34  | 6.9         | 5.18  | 0.25%               |
| 43  | 7           | 5.2   | 41.4        | 6.23  | 33.9        | 3.11  | 0.2         | 9.34  | 0.3         | 7.26  | 0.17%               |
| 44  | 5.8         | 5.32  | 35          | 6.09  | 34.2        | 3.23  | 2.5         | 6.81  | 10.5        | 7.31  | 0.21%               |
| 45  | 10.6        | 5.56  | 34.7        | 6     | 34.5        | 3.7   | 5.2         | 7.8   | 7.5         | 7.1   | 0.22%               |
| 46  | 13.7        | 12.96 | 33          | 5.34  | 35.4        | 2.66  | 2.6         | 2.63  | 6.8         | 3.69  | 0.23%               |
| 47  | 18.6        | 5.71  | 31.1        | 5.91  | 35.5        | 3.97  | 12.6        | 6.16  | 3.5         | 7     | 0.25%               |
| 48  | 20.6        | 5.95  | 34.3        | 5.58  | 35.6        | 4.16  | 12.1        | 7.48  | 2.6         | 7.21  | 0.26%               |
| 49  | 18.8        | 7.26  | 45.4        | 4.05  | 36.4        | 5.09  | 5.1         | 6.09  | 13.5        | 8.13  | 0.27%               |
| 50  | 9.4         | 3.63  | 22.7        | 3.12  | 37.3        | 2.6   | 2.6         | 2.6   | 6.8         | 3.63  | 0.19%               |
| 51  | 12.3        | 5.68  | 29.4        | 6.03  | 38.7        | 4.03  | 10.1        | 7.19  | 14.7        | 6.84  | 0.27%               |
| 52  | 6.2         | 12.96 | 36.3        | 5.34  | 39.1        | 2.66  | 9.4         | 2.63  | 6.8         | 3.69  | 0.21%               |
| 53  | 19.1        | 6.23  | 42.9        | 6.23  | 40.3        | 6.23  | 3.7         | 6.23  | 19          | 6.23  | 0.32%               |
| 54  | 6           | 5.64  | 27.7        | 6.16  | 41.8        | 4.1   | 7.7         | 8.22  | 25.9        | 6.67  | 0.27%               |
| 55  | 36.5        | 5.76  | 32.2        | 6.02  | 43          | 4.22  | 24          | 7.24  | 5           | 6.72  | 0.36%               |
| 56  | 42.1        | 5.21  | 32.4        | 5.73  | 43.8        | 6.76  | 13.6        | 6.25  | 2.2         | 7.28  | 0.33%               |
| 57  | 109.3       | 5.26  | 107.8       | 4.19  | 44.5        | 7.34  | 0.1         | 6.3   | 0.1         | 8.41  | 0.55%               |
| 58  | 9.3         | 5.44  | 37          | 5.96  | 44.9        | 3.36  | 4.8         | 8.42  | 20.8        | 7.37  | 0.28%               |
| 59  | 8.2         | 5.72  | 38          | 6.23  | 47.6        | 4.67  | 13          | 7.79  | 39.4        | 6.75  | 0.36%               |
| 60  | 41.9        | 4.14  | 38.1        | 8.32  | 48.6        | 4.14  | 12.3        | 5.2   | 5           | 9.34  | 0.33%               |
| 61  | 5.3         | 6.23  | 31.1        | 6.23  | 49.5        | 6.23  | 18.7        | 6.23  | 41          | 6.23  | 0.38%               |
| 62  | 164.1       | 4.71  | 167.2       | 5.76  | 50.1        | 8.37  | 0.2         | 5.74  | 0.2         | 6.81  | 0.89%               |
| 63  | 41.5        | 6.23  | 27.3        | 7.26  | 51.4        | 5.2   | 22.1        | 5.2   | 4.4         | 7.26  | 0.36%               |
| 64  | 50.3        | 6.16  | 25.9        | 6.67  | 53.1        | 5.14  | 35          | 6.15  | 7.1         | 6.67  | 0.44%               |
| 65  | 58.4        | 4.05  | 35.1        | 5.08  | 56.4        | 4.05  | 29.4        | 6.08  | 2.6         | 11.16 | 0.37%               |
| 66  | 50.3        | 6.16  | 25.9        | 6.67  | 57.5        | 5.14  | 35          | 6.15  | 7.1         | 6.67  | 0.45%               |
| 67  | 59          | 6.08  | 24.5        | 6.08  | 59.7        | 5.08  | 47.8        | 7.09  | 9.8         | 6.08  | 0.53%               |
| 68  | 62          | 5.07  | 29.8        | 5.58  | 63.1        | 4.57  | 43          | 6.59  | 9.6         | 8.62  | 0.48%               |
| 69  | 11          | 5.2   | 44.9        | 6.23  | 65.7        | 3.11  | 7.3         | 9.34  | 37.7        | 7.26  | 0.37%               |
| 70  | 45.2        | 4.15  | 34          | 6.25  | 75.5        | 7.28  | 50.2        | 7.28  | 35.5        | 6.28  | 0.63%               |
| 71  | 63.1        | 5.21  | 48.5        | 5.99  | 75.7        | 5.99  | 20.4        | 6.25  | 3.2         | 7.8   | 0.51%               |
| 72  | 135.4       | 7.34  | 133.7       | 7.34  | 92.6        | 6.3   | 36.5        | 4.22  | 31.3        | 6.3   | 1.18%               |
| 73  | 135.4       | 5.21  | 151.9       | 6.25  | 97.7        | 6.25  | 30.6        | 7.28  | 44.4        | 6.25  | 1.14%               |
| 74  | 68.3        | 4.71  | 72.3        | 5.76  | 101         | 8.37  | 45.7        | 5.74  | 46.1        | 6.81  | 0.88%               |
| 75  | 105.4       | 6.21  | 101.6       | 5.21  | 101.6       | 8.34  | 0.1         | 8.34  | 0.2         | 3.12  | 0.84%               |
| 76  | 84.8        | 4.58  | 72.4        | 6.85  | 103.8       | 9.16  | 39.4        | 4.58  | 36.3        | 6.85  | 0.89%               |
| 77  | 83.8        | 6.95  | 166.6       | 6.95  | 110.5       | 4.16  | 0.2         | 6.95  | 0.2         | 7.01  | 0.89%               |
| 78  | 226         | 7.34  | 244.2       | 7.34  | 116         | 6.3   | 0.2         | 4.22  | 0.1         | 6.3   | 1.67%               |
| 79  | 195.1       | 5.26  | 202.3       | 5.26  | 119.9       | 9.45  | 44.4        | 5.26  | 48.2        | 8.41  | 1.47%               |
| 80  | 122.4       | 5.21  | 109.5       | 5.73  | 120         | 6.76  | 38          | 6.25  | 21.7        | 7.28  | 1.02%               |
| 81  | 91.4        | 5.26  | 110.5       | 5.26  | 130         | 9.45  | 41.1        | 4.19  | 56.7        | 7.34  | 1.17%               |
| 82  | 90.4        | 5.26  | 67.7        | 4.19  | 130.4       | 7.34  | 88.8        | 6.3   | 62.6        | 8.41  | 1.14%               |
| 83  | 47.5        | 6.85  | 12.4        | 6.85  | 141.3       | 6.85  | 58.5        | 6.85  | 34.5        | 4.61  | 0.76%               |
| 84  | 99.8        | 6.25  | 98          | 6.25  | 161.1       | 6.25  | 123.1       | 5.21  | 117.8       | 7.28  | 1.54%               |
| 85  | 160.6       | 5.21  | 154.3       | 5.21  | 163.9       | 8.31  | 48.8        | 6.25  | 39          | 6.25  | 1.47%               |
| 86  | 101.4       | 11.43 | 137.4       | 3.12  | 174         | 5.21  | 66.2        | 5.21  | 98.7        | 6.25  | 1.43%               |
| 87  | 252.3       | 5.21  | 154.2       | 7.28  | 183.7       | 5.21  | 160.9       | 5.74  | 59.3        | 5.18  | 2.08%               |
| 88  | 121.6       | 6.3   | 107.9       | 5.26  | 194.3       | 8.38  | 110.8       | 6.3   | 93.6        | 5.26  | 1.68%               |
| 89  | 194         | 6.85  | 117         | 4.58  | 254.5       | 6.3   | 131         | 6.85  | 60          | 6.3   | 1.93%               |
| 90  | 270.5       | 6.36  | 205         | 6.36  | 255.9       | 4.23  | 79.1        | 6.36  | 10.1        | 8.49  | 1.87%               |

The main factors affecting the deformation of sandy shale include excavation method ( $F_1$ ), initial support strength ( $F_2$ ), closure time ( $F_3$ ), tunnel burial depth ( $F_4$ ), lithological indicators ( $F_5$ ), rock integrity ( $F_6$ ), groundwater conditions ( $F_7$ ), relative orientation between major structural planes and tunnels ( $F_8$ ). Based on the engineering geological conditions and construction parameters of 90 excavated tunnel sections, statistical analysis and classification were conducted on the various parameters influencing asymmetric defor-

mation in sandy shale tunnels, as shown in Tables 3–5. To construct the model inputs, the engineering parameters were quantified according to the classification criteria in Tables 3–5. Closure time and tunnel burial depth were retained as measured numerical variables. The remaining variables were converted into classification grades based on the engineering descriptions of each tunnel section. Excavation method and initial support strength describe the construction and support conditions. Lithology, rock integrity, groundwater condition, and the relative orientation between major structural planes and the tunnel describe the geological and hydrogeological setting. This coding scheme provides a consistent numerical form for the field records while preserving the engineering meaning of each grade.

**Table 3.** Classification of support strength.

| Grade | Composite Support Type | Steel Arches and Their Spacing (m) | Number and Length of Advanced Small Conduits (m) | Number and Length of Anchor Rods (m) | Spray Concrete Thickness (cm) |
|-------|------------------------|------------------------------------|--------------------------------------------------|--------------------------------------|-------------------------------|
| I     | III                    | I18, 1                             | Φ42, 40, 4.5                                     | Φ22, 13, 3.5                         | C35, 25                       |
| II    | IV                     | I20, 0.6                           | Φ42, 50, 4                                       | Φ22, 13, 4                           | C35, 28                       |
| III   | V                      | I22, 0.6                           | Φ42, 50, 4                                       | Φ22, 12, 4                           | C35, 29                       |
| IV    | V                      | H175, 0.6                          | Φ42, 50, 5                                       | Φ25, 16, 4                           | C35, 29                       |
| V     | V                      | H175, 0.6                          | Regional section grouting                        | Φ25, 18, 4                           | C35, 29                       |

**Table 4.** Classification criteria for relative orientation between major structural planes and tunnels.

| Grade                  | I                                                            | II                                                        | III  | IV                                                           | V                                                         |
|------------------------|--------------------------------------------------------------|-----------------------------------------------------------|------|--------------------------------------------------------------|-----------------------------------------------------------|
| Occurrence combination | $85^\circ \leq d_1 \leq 90^\circ$<br>and $d_2 \geq 60^\circ$ | $75^\circ \leq d_1 < 85^\circ$<br>and $d_2 \geq 60^\circ$ | Else | $30^\circ \leq d_1 \leq 50^\circ$<br>and $d_2 \leq 30^\circ$ | $50^\circ < d_1 \leq 75^\circ$<br>and $d_2 \leq 30^\circ$ |

**Table 5.** Classification of other factors.

| Grade | Excavation Method                        | Groundwater Condition | Lithological Indicators | Rock Integrity    |
|-------|------------------------------------------|-----------------------|-------------------------|-------------------|
| I     | Full-face method                         | Dry                   | Extremely hard rock     | Intact            |
| II    | Double-step method                       | Slightly wet          | Hard rock               | Relatively intact |
| III   | Three-step method                        | Wet                   | Softer rock             | Relatively broken |
| IV    | Three-bench seven-step excavation method | Linear seepage        | Soft rock               | Broken            |
| V     | CRD method                               | Water inrush          | Extremely soft rock     | Extremely broken  |

### 3.3. Sample Database Construction

The eight engineering variables defined in Section 3.2 were used as model inputs, and the mean relative deformation was used as the prediction target. A development dataset comprising 90 sandy shale tunnel sections was constructed, as summarized in Table 6.

**Table 6.** Sample set of deformation data for sandy shale tunnels.

| No. | $F_1$ | $F_2$ | $F_3$ | $F_4$ | $F_5$ | $F_6$ | $F_7$ | $F_8$ | $\bar{\varepsilon}$ |
|-----|-------|-------|-------|-------|-------|-------|-------|-------|---------------------|
| 1   | 2     | 1     | 31    | 141   | 2     | 3     | 1     | 3     | 0.13%               |
| 2   | 2     | 1     | 32    | 142   | 2     | 3     | 1     | 3     | 0.15%               |
| 3   | 2     | 1     | 31    | 143   | 2     | 3     | 1     | 3     | 0.15%               |
| 4   | 2     | 1     | 29    | 143   | 2     | 3     | 1     | 3     | 0.14%               |
| 5   | 2     | 1     | 30    | 143   | 2     | 3     | 1     | 3     | 0.15%               |
| 6   | 2     | 1     | 31    | 144   | 2     | 3     | 1     | 3     | 0.15%               |
| 7   | 2     | 1     | 32    | 146   | 2     | 3     | 1     | 3     | 0.15%               |
| 8   | 1     | 1     | 25    | 303   | 3     | 3     | 1     | 3     | 0.13%               |
| 9   | 1     | 1     | 24    | 317   | 3     | 3     | 1     | 3     | 0.13%               |
| 10  | 1     | 1     | 26    | 305   | 3     | 3     | 1     | 4     | 0.13%               |
| 11  | 1     | 1     | 26    | 306   | 3     | 3     | 1     | 4     | 0.14%               |

Table 6. Cont.

| No. | $F_1$ | $F_2$ | $F_3$ | $F_4$ | $F_5$ | $F_6$ | $F_7$ | $F_8$ | $\bar{\varepsilon}$ |
|-----|-------|-------|-------|-------|-------|-------|-------|-------|---------------------|
| 12  | 1     | 1     | 27    | 300   | 3     | 3     | 1     | 3     | 0.13%               |
| 13  | 1     | 1     | 27    | 308   | 3     | 3     | 1     | 3     | 0.14%               |
| 14  | 1     | 1     | 26    | 302   | 3     | 3     | 1     | 3     | 0.14%               |
| 15  | 1     | 1     | 25    | 305   | 3     | 3     | 1     | 3     | 0.14%               |
| 16  | 1     | 1     | 25    | 300   | 3     | 3     | 1     | 4     | 0.14%               |
| 17  | 1     | 1     | 26    | 302   | 3     | 3     | 1     | 3     | 0.16%               |
| 18  | 4     | 3     | 25    | 241.6 | 3     | 3     | 3     | 3     | 0.10%               |
| 19  | 4     | 3     | 24    | 241   | 3     | 3     | 2     | 3     | 0.12%               |
| 20  | 3     | 3     | 36    | 164   | 3     | 3     | 3     | 3     | 0.22%               |
| 21  | 1     | 1     | 26    | 306   | 3     | 3     | 1     | 3     | 0.14%               |
| 22  | 1     | 1     | 26    | 308   | 3     | 3     | 1     | 3     | 0.18%               |
| 23  | 3     | 2     | 24    | 95    | 3     | 3     | 4     | 3     | 0.23%               |
| 24  | 3     | 2     | 27    | 152.5 | 3     | 3     | 3     | 3     | 0.14%               |
| 25  | 3     | 2     | 24    | 98    | 2     | 3     | 3     | 3     | 0.20%               |
| 26  | 4     | 3     | 27    | 242.4 | 3     | 3     | 3     | 3     | 0.14%               |
| 27  | 3     | 2     | 23    | 96    | 3     | 3     | 3     | 3     | 0.15%               |
| 28  | 3     | 2     | 31    | 143   | 3     | 3     | 3     | 3     | 0.18%               |
| 29  | 3     | 2     | 45    | 155   | 3     | 3     | 3     | 3     | 0.11%               |
| 30  | 4     | 3     | 25    | 244   | 3     | 3     | 3     | 3     | 0.17%               |
| 31  | 3     | 2     | 25    | 99    | 3     | 3     | 4     | 3     | 0.17%               |
| 32  | 3     | 2     | 24    | 96    | 3     | 3     | 4     | 3     | 0.18%               |
| 33  | 3     | 2     | 30    | 144   | 3     | 3     | 3     | 3     | 0.26%               |
| 34  | 2     | 1     | 16    | 248   | 3     | 3     | 1     | 4     | 0.16%               |
| 35  | 2     | 2     | 18    | 248   | 3     | 3     | 2     | 4     | 0.17%               |
| 36  | 3     | 2     | 33    | 347   | 3     | 3     | 4     | 4     | 0.20%               |
| 37  | 3     | 2     | 32    | 342   | 3     | 3     | 4     | 3     | 0.20%               |
| 38  | 3     | 2     | 32    | 337   | 3     | 3     | 4     | 3     | 0.18%               |
| 39  | 3     | 3     | 23    | 239   | 2     | 3     | 2     | 3     | 0.23%               |
| 40  | 3     | 2     | 32    | 332   | 3     | 3     | 4     | 3     | 0.19%               |
| 41  | 3     | 3     | 23    | 181.5 | 3     | 3     | 3     | 3     | 0.28%               |
| 42  | 3     | 3     | 27    | 184.5 | 3     | 3     | 3     | 3     | 0.25%               |
| 43  | 3     | 3     | 32    | 168   | 3     | 3     | 3     | 5     | 0.17%               |
| 44  | 3     | 2     | 31    | 327   | 3     | 3     | 4     | 4     | 0.21%               |
| 45  | 3     | 2     | 30    | 322   | 3     | 3     | 4     | 3     | 0.22%               |
| 46  | 3     | 2     | 31    | 148   | 3     | 3     | 3     | 3     | 0.23%               |
| 47  | 3     | 2     | 30    | 321   | 3     | 3     | 3     | 4     | 0.25%               |
| 48  | 3     | 2     | 51    | 244   | 3     | 2     | 1     | 3     | 0.26%               |
| 49  | 3     | 3     | 34    | 158   | 3     | 3     | 3     | 3     | 0.27%               |
| 50  | 3     | 3     | 26    | 182.5 | 3     | 3     | 3     | 3     | 0.19%               |
| 51  | 3     | 2     | 52    | 265   | 3     | 2     | 1     | 3     | 0.27%               |
| 52  | 3     | 2     | 34    | 146   | 3     | 3     | 3     | 3     | 0.21%               |
| 53  | 3     | 3     | 26    | 178.5 | 3     | 3     | 3     | 3     | 0.32%               |
| 54  | 3     | 2     | 52    | 254   | 3     | 2     | 1     | 3     | 0.27%               |
| 55  | 3     | 1     | 48    | 250   | 3     | 2     | 1     | 4     | 0.36%               |
| 56  | 3     | 2     | 75    | 93    | 3     | 3     | 3     | 4     | 0.33%               |
| 57  | 3     | 3     | 49    | 90.5  | 3     | 3     | 2     | 3     | 0.55%               |
| 58  | 3     | 2     | 50    | 251   | 3     | 2     | 1     | 3     | 0.28%               |
| 59  | 3     | 3     | 24    | 180.5 | 3     | 3     | 3     | 3     | 0.36%               |
| 60  | 4     | 3     | 24    | 240   | 3     | 3     | 2     | 3     | 0.33%               |
| 61  | 3     | 3     | 24    | 173.5 | 3     | 3     | 3     | 3     | 0.38%               |
| 62  | 3     | 2     | 47    | 66.5  | 3     | 3     | 2     | 3     | 0.89%               |
| 63  | 4     | 3     | 26    | 239.2 | 3     | 3     | 2     | 3     | 0.36%               |
| 64  | 2     | 2     | 32    | 236   | 3     | 3     | 3     | 3     | 0.44%               |
| 65  | 2     | 2     | 49    | 235.2 | 3     | 3     | 2     | 3     | 0.37%               |
| 66  | 2     | 2     | 28    | 237.6 | 3     | 3     | 4     | 3     | 0.45%               |
| 67  | 2     | 2     | 51    | 234.4 | 3     | 3     | 2     | 3     | 0.53%               |
| 68  | 4     | 3     | 25    | 238.4 | 3     | 3     | 4     | 3     | 0.48%               |
| 69  | 3     | 3     | 33    | 171   | 3     | 3     | 3     | 5     | 0.37%               |
| 70  | 3     | 2     | 73    | 69.5  | 3     | 3     | 3     | 3     | 0.63%               |

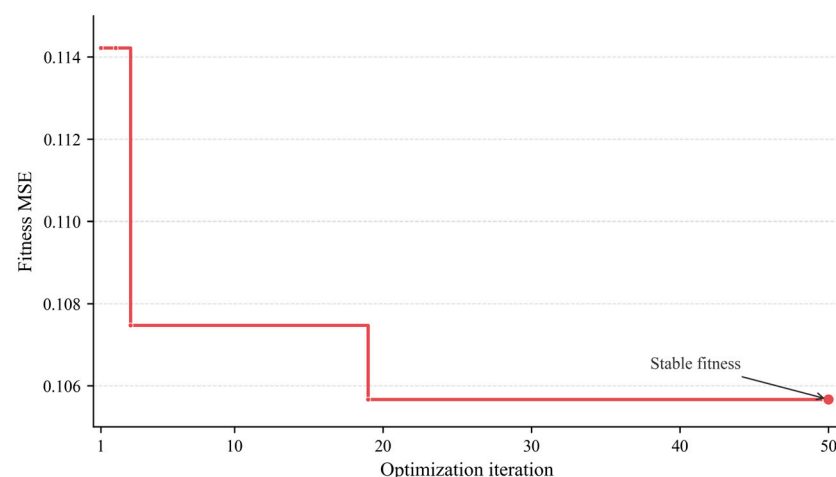
Table 6. Cont.

| No. | $F_1$ | $F_2$ | $F_3$ | $F_4$ | $F_5$ | $F_6$ | $F_7$ | $F_8$ | $\bar{\varepsilon}$ |
|-----|-------|-------|-------|-------|-------|-------|-------|-------|---------------------|
| 71  | 3     | 2     | 79    | 88.5  | 3     | 3     | 3     | 5     | 0.51%               |
| 72  | 3     | 3     | 45    | 101.5 | 3     | 3     | 2     | 3     | 1.18%               |
| 73  | 3     | 2     | 81    | 66    | 3     | 3     | 3     | 3     | 1.14%               |
| 74  | 3     | 2     | 43    | 93.5  | 3     | 3     | 2     | 3     | 0.88%               |
| 75  | 3     | 2     | 83    | 77    | 3     | 3     | 3     | 5     | 0.84%               |
| 76  | 3     | 4     | 64    | 123   | 4     | 4     | 3     | 3     | 0.89%               |
| 77  | 3     | 2     | 60    | 75.5  | 4     | 3     | 2     | 3     | 0.89%               |
| 78  | 3     | 4     | 68    | 118   | 4     | 5     | 3     | 3     | 1.67%               |
| 79  | 3     | 3     | 41    | 96.5  | 4     | 3     | 2     | 3     | 1.47%               |
| 80  | 3     | 2     | 81    | 84    | 3     | 3     | 3     | 5     | 1.02%               |
| 81  | 3     | 3     | 58    | 84.5  | 3     | 3     | 2     | 3     | 1.17%               |
| 82  | 3     | 3     | 32    | 87.5  | 3     | 3     | 2     | 3     | 1.14%               |
| 83  | 3     | 4     | 36    | 125   | 4     | 4     | 3     | 3     | 0.76%               |
| 84  | 3     | 2     | 96    | 78.5  | 4     | 3     | 2     | 3     | 1.54%               |
| 85  | 3     | 2     | 79    | 73.5  | 4     | 4     | 3     | 3     | 1.47%               |
| 86  | 3     | 2     | 66    | 72.5  | 4     | 3     | 2     | 3     | 1.43%               |
| 87  | 3     | 2     | 38    | 66    | 3     | 3     | 2     | 3     | 2.08%               |
| 88  | 3     | 3     | 75    | 81.5  | 4     | 3     | 2     | 3     | 1.68%               |
| 89  | 3     | 4     | 65    | 121   | 4     | 5     | 3     | 3     | 1.93%               |
| 90  | 3     | 3     | 30    | 68    | 4     | 5     | 3     | 3     | 1.87%               |

## 4. Results

### 4.1. Optimization Trajectory Analysis

Figure 3 presents the best-so-far fitness MSE obtained during the 50-iteration NWOA hyperparameter search. The fitness MSE was 0.1142 during the first two iterations, decreasing to 0.1075 at iteration 3, and further decreasing to 0.1057 at iteration 19. No candidate evaluated during iterations 20–50 achieved a lower validation MSE, and the best-so-far fitness therefore remained unchanged through the end of the search. The trajectory shows that the principal improvements occurred during the early and intermediate stages of optimization and that the selected solution remained stable within the specified search budget.



**Figure 3.** Best-so-far fitness MSE during the 50-iteration NWOA-based hyperparameter search.

### 4.2. Prediction Accuracy and Error Distribution

For the fixed case analysis, the predicted deformation rates were compared with the measured values for six predefined sections. The detailed numerical data are listed in Table 7, and the visual comparison is presented in Figure 4.

**Table 7.** Engineering parameters and deformation prediction results for the six case-validation samples.

| No. | $F_1$ | $F_2$ | $F_3$ | $F_4$ | $F_5$ | $F_6$ | $F_7$ | $F_8$ | Measured Deformation Rate (%) | Predicted Deformation Rate (%) |
|-----|-------|-------|-------|-------|-------|-------|-------|-------|-------------------------------|--------------------------------|
| 1   | 1     | 1     | 24    | 307   | 3     | 3     | 1     | 4     | 0.14%                         | 0.21%                          |
| 2   | 2     | 1     | 17    | 249   | 3     | 3     | 1     | 4     | 0.19%                         | 0.22%                          |
| 3   | 3     | 2     | 48    | 258   | 3     | 2     | 1     | 3     | 0.35%                         | 0.22%                          |
| 4   | 3     | 2     | 80    | 79.5  | 3     | 3     | 3     | 5     | 0.63%                         | 0.88%                          |
| 5   | 3     | 3     | 77    | 70.5  | 4     | 3     | 3     | 3     | 1.77%                         | 1.41%                          |
| 6   | 3     | 3     | 101   | 63    | 4     | 5     | 1     | 3     | 3.80%                         | 3.82%                          |

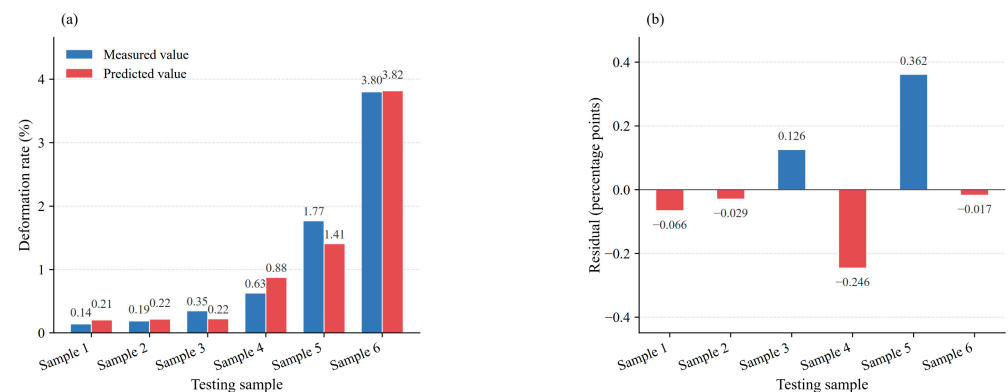
**Figure 4.** Prediction and residual analysis of NWOA-LSTM on the testing samples: (a) measured and predicted deformation values; (b) residuals calculated as measured values minus predicted values.

Figure 4a compares the measured and predicted deformation values of the six testing samples. For the small-deformation samples, the measured values ranged from 0.14% to 0.35%, and the predicted values were 0.2060%, 0.2195%, and 0.2243%, respectively. For Sample 4, where the measured deformation value was 0.63%, the model predicted 0.8759%, showing an overestimation of the transitional deformation level. For the large-deformation samples, the measured values of Samples 5 and 6 were 1.77% and 3.80%, and the corresponding predicted values were 1.4083% and 3.8174%, respectively.

A residual analysis was further conducted, as shown in Figure 4b. The residuals were calculated as the measured values minus the predicted values. The residuals ranged from  $-0.2459$  to  $0.3617$  percentage points, with a mean residual of  $0.0215$  percentage points. The maximum absolute error was  $0.3617$  percentage points, which occurred in Sample 5. The residuals were distributed around zero, indicating that the model did not show an obvious one-sided overestimation or underestimation tendency for the testing samples. Given the limited number of case validation samples, the source of the relatively large residuals cannot be isolated from the present analysis. These residuals may reflect section-specific conditions that were not fully represented by the eight input variables.

## 5. Discussion

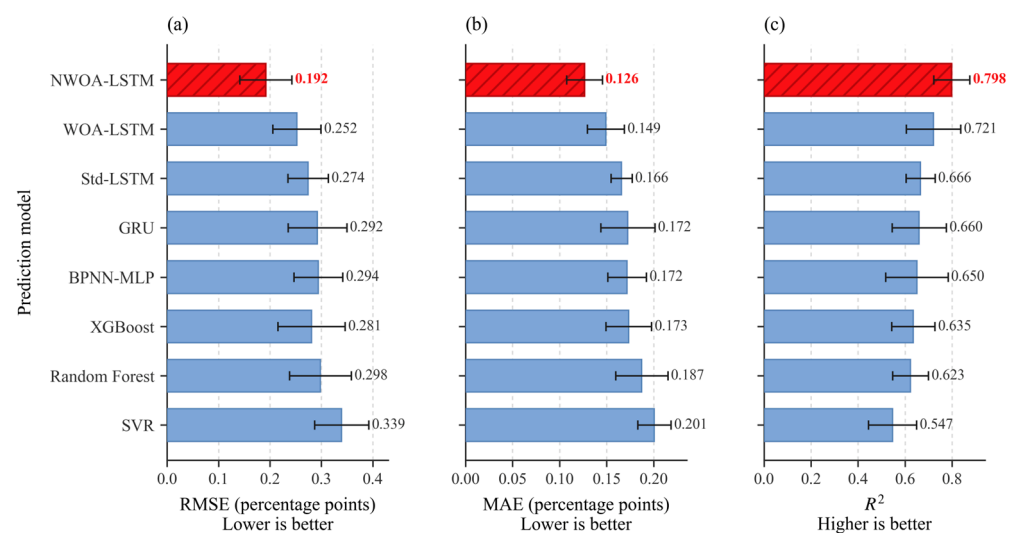
### 5.1. Comparison with Benchmark Models

To provide a comprehensive evaluation, the proposed NWOA-LSTM model was compared with SVR, Random Forest, XGBoost, BPNN-MLP, WOA-LSTM, standard LSTM, and GRU. All models were evaluated using the same ten stratified 80:20 partitions of the 90-section development dataset. For each partition, preprocessing parameters were estimated from the training subset and subsequently applied to the corresponding evaluation subset. RMSE, MAE, and  $R^2$  were calculated on the original deformation-rate scale after inverse transformation and are reported as mean  $\pm$  standard deviation.

As shown in Table 8 and Figure 5, NWOA-LSTM achieved the lowest mean RMSE of  $0.1921 \pm 0.0506$  percentage points, the lowest mean MAE of  $0.1264 \pm 0.0190$  percentage points, and the highest mean  $R^2$  of  $0.7981 \pm 0.0766$ . Compared with WOA-LSTM, NWOA-LSTM reduced RMSE and MAE by 23.9% and 15.2%, respectively, while increasing  $R^2$  by 0.0775. Compared with standard LSTM, the corresponding reductions in RMSE and MAE were 29.9% and 23.8%, and  $R^2$  increased by 0.1324. These repeated-partition results demonstrate that the proposed optimization strategy improved the prediction accuracy and variance-explanation capability of the LSTM model across different data compositions.

**Table 8.** Repeated-partition performance of the benchmark models on the 90-section development dataset.

| Model         | RMSE<br>(Percentage Points) | MAE<br>(Percentage Points) | $R^2$               |
|---------------|-----------------------------|----------------------------|---------------------|
| SVR           | $0.3393 \pm 0.0527$         | $0.2006 \pm 0.0177$        | $0.5466 \pm 0.1022$ |
| Random Forest | $0.2982 \pm 0.0600$         | $0.1873 \pm 0.0277$        | $0.6226 \pm 0.0762$ |
| XGBoost       | $0.2807 \pm 0.0653$         | $0.1734 \pm 0.0243$        | $0.6347 \pm 0.0919$ |
| BPNN-MLP      | $0.2942 \pm 0.0474$         | $0.1717 \pm 0.0205$        | $0.6500 \pm 0.1326$ |
| WOA-LSTM      | $0.2523 \pm 0.0469$         | $0.1491 \pm 0.0196$        | $0.7206 \pm 0.1159$ |
| Std-LSTM      | $0.2742 \pm 0.0394$         | $0.1658 \pm 0.0112$        | $0.6657 \pm 0.0613$ |
| GRU           | $0.2923 \pm 0.0572$         | $0.1725 \pm 0.0287$        | $0.6597 \pm 0.1154$ |
| NWOA-LSTM     | $0.1921 \pm 0.0506$         | $0.1264 \pm 0.0190$        | $0.7981 \pm 0.0766$ |



**Figure 5.** Repeated-partition performance of the benchmark models: (a) RMSE; (b) MAE; and (c)  $R^2$ .

## 5.2. Comparison with a Parameter-Matched MLP

To examine the contribution of the gated regression structure under comparable model capacity, an additional parameter-matched MLP was constructed. The MLP contained two fully connected hidden layers, and the hidden-layer width was adjusted so that its trainable parameter count differed from that of NWOA-LSTM by less than 1%. The parameter-matched MLP and NWOA-LSTM were evaluated using the same ten repeated data partitions, preprocessing procedure, optimizer settings, learning rate, regularization coefficient, dropout rate, training epochs, and batch size.

Across the ten repeated partitions, the parameter-matched MLP achieved an RMSE of  $0.2942 \pm 0.0474$  percentage points, an MAE of  $0.1717 \pm 0.0205$  percentage points, and an  $R^2$  of  $0.6500 \pm 0.1326$ . NWOA-LSTM achieved an RMSE of  $0.1921 \pm 0.0506$  percentage points, an MAE of  $0.1264 \pm 0.0190$  percentage points, and an  $R^2$  of  $0.7981 \pm 0.0766$ . Compared with the parameter-matched MLP, NWOA-LSTM reduced RMSE and MAE by 34.7% and 26.4%, respectively, and increased  $R^2$  by 0.1481. These results show that the improvement

achieved by NWOA-LSTM was not attributable solely to model size. The gated nonlinear representation provided a more effective mapping between the engineering variables and tunnel deformation for the investigated dataset.

### 5.3. Ablation Analysis of NWOA-LSTM

To evaluate the contributions of the proposed NWOA strategies, NWOA-LSTM, WOA-LSTM, standard LSTM, and the two ablated variants were evaluated using the same ten stratified 80:20 partitions of the 90-section development dataset. All variants used identical data partitions, preprocessing procedures, model inputs, and evaluation metrics.

As shown in Table 9, NWOA-LSTM achieved the lowest mean RMSE and MAE and the highest mean  $R^2$ . Removing the dynamic spiral updating mechanism increased the mean RMSE from 0.1921 to 0.2126, whereas removing the adaptive weight increased it to 0.2238. The corresponding mean  $R^2$  values decreased from 0.7981 to 0.7209 and 0.7108, respectively. These repeated-partition results indicate that both strategies contributed to prediction performance, with the adaptive weight producing the larger numerical change.

**Table 9.** Repeated-partition ablation performance of NWOA-LSTM and its variants on the 90-section development dataset.

| Model                   | RMSE<br>(Percentage Points) | MAE<br>(Percentage Points) | $R^2$               |
|-------------------------|-----------------------------|----------------------------|---------------------|
| NWOA-LSTM               | 0.1921 $\pm$ 0.0506         | 0.1264 $\pm$ 0.0190        | 0.7981 $\pm$ 0.0766 |
| Without dynamic spiral  | 0.2126 $\pm$ 0.0446         | 0.1384 $\pm$ 0.0205        | 0.7209 $\pm$ 0.0908 |
| Without adaptive weight | 0.2238 $\pm$ 0.0514         | 0.1382 $\pm$ 0.0245        | 0.7108 $\pm$ 0.1126 |
| Std-LSTM                | 0.2742 $\pm$ 0.0394         | 0.1658 $\pm$ 0.0112        | 0.6657 $\pm$ 0.0613 |
| WOA-LSTM                | 0.2523 $\pm$ 0.0469         | 0.1491 $\pm$ 0.0196        | 0.7206 $\pm$ 0.1159 |

### 5.4. Cross-Validation Performance

Two repetitions of stratified five-fold cross-validation were conducted to evaluate the NWOA-LSTM model across the 90 development sections. As summarized in Table 10, the model achieved an RMSE of 0.2294  $\pm$  0.0734 percentage points, an MAE of 0.1427  $\pm$  0.0350 percentage points, and an  $R^2$  of 0.8660  $\pm$  0.0548 across the ten outer folds. Each development section was included in an outer test fold twice, providing repeated evaluation coverage of the complete development dataset.

**Table 10.** Cross-validation performance of the NWOA-LSTM model.

| Validation Procedure                                                         | Outer-Fold<br>Evaluations (n) | RMSE<br>(Percentage Points) | MAE<br>(Percentage Points) | $R^2$               |
|------------------------------------------------------------------------------|-------------------------------|-----------------------------|----------------------------|---------------------|
| Repeated stratified<br>five-fold cross-validation (2 $\times$ 5-fold)        | 10                            | 0.2294 $\pm$ 0.0734         | 0.1427 $\pm$ 0.0350        | 0.8660 $\pm$ 0.0548 |
| Nested stratified<br>cross-validation (5 outer folds $\times$ 3 inner folds) | 5                             | 0.2219 $\pm$ 0.0751         | 0.1505 $\pm$ 0.0585        | 0.8732 $\pm$ 0.0599 |

Nested stratified cross-validation with five outer folds and three inner folds produced an RMSE of 0.2219  $\pm$  0.0751 percentage points, an MAE of 0.1505  $\pm$  0.0585 percentage points, and an  $R^2$  of 0.8732  $\pm$  0.0599. The comparable performance estimates obtained using the two validation procedures indicate that the NWOA-LSTM model maintained consistent project-scale prediction performance across different fold structures and hyperparameter-selection procedures.

## 6. Conclusions

This study developed and evaluated an NWOA-LSTM deformation prediction framework using field-monitoring data from the investigated sandy shale tunnel project. Based

on the tunnel-section data and validation procedures adopted in this project, the following conclusions are drawn:

(1) A tunnel deformation prediction dataset was constructed using eight engineering factors, including excavation method, initial support strength, closure time, tunnel burial depth, lithology, rock integrity, groundwater condition, and the relative orientation between major structural planes and the tunnel. The LSTM input was organized as a single-step sequence, and the model was used as a gated nonlinear regression model for tunnel-section-based deformation prediction.

(2) The NWOA-based hyperparameter search reduced the best fitness MSE from 0.1142 to 0.1057 and maintained a stable solution during the subsequent iterations. The repeated-partition ablation analysis showed that removing the dynamic spiral updating mechanism and the adaptive weight coefficient increased the mean RMSE from 0.1921 to 0.2126 and 0.2238, respectively, indicating that both strategies contributed to the predictive performance of the complete NWOA-LSTM model.

(3) Across ten stratified 80:20 repeated partitions, NWOA-LSTM achieved the best overall predictive performance among the evaluated models, with the lowest mean RMSE of  $0.1921 \pm 0.0506$  percentage points and MAE of  $0.1264 \pm 0.0190$  percentage points. Compared with WOA-LSTM, RMSE and MAE were reduced by 23.9% and 15.2%, respectively. Repeated and nested cross-validation yielded RMSE values of  $0.2294 \pm 0.0734$  and  $0.2219 \pm 0.0751$  percentage points, MAE values of  $0.1427 \pm 0.0350$  and  $0.1505 \pm 0.0585$  percentage points, and  $R^2$  values of  $0.8660 \pm 0.0548$  and  $0.8732 \pm 0.0599$ , respectively. The comparable results obtained using the two validation procedures support stable project-specific predictive performance for the investigated sandy shale tunnel. Future multi-project validation will further examine model performance under different geological and construction conditions.

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