Gray relational analysis and SBOA-BP for predicting settlement intervals of high-speed railway subgrade

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Abstract

Purpose – The deformation of the roadbed is easily influenced by the external environment to improve the accuracy of high-speed railway subgrade settlement prediction.

Design/methodology/approach – A high-speed railway subgrade settlement interval prediction method using the secretary bird optimization (SBOA) algorithm to optimize the BP neural network under the premise of gray relational analysis is proposed.

Findings – Using the SBOA algorithm to optimize the BP neural network, the optimal weights and thresholds are obtained, and the best parameter prediction model is combined. The data were collected from the sensors deployed through the subgrade settlement monitoring system, and the gray relational analysis is used to verify that all four influencing factors had a great correlation to the subgrade settlement, and the collected data are verified using the model.

Originality/value – The experimental results show that the SBOA-BP model has higher prediction accuracy than the BP model, and the SBOA-BP model has a wider range of prediction intervals for a given confidence level, which can provide higher guiding value for practical engineering applications.

Keywords Gray relational analysis, Secretary bird optimization algorithm, Backpropagation neural network, Subgrade settlement, Interval prediction

Paper type Research paper

1. Introduction

In the operation stage of high-speed railway, uneven settlement of roadbed occurs due to many factors. Especially in the northwestern region where the temperature difference between day and night is large, the temperature and humidity have a greater impact on the settlement of the roadbed. Settlement of roadbed seriously threatens the safety of passengers and travellers. Therefore, the prediction of roadbed settlement can provide timely maintenance plan for the railway transport department and play a key role in the smooth operation of trains.

Scholars at home and abroad now mostly use artificial intelligence methods such as mathematical statistics, machine learning to predict subgrade settlement, which improves the prediction accuracy to a certain extent compared with the previous traditional methods, but there are still shortcomings. Jin and He (2016) used Markov state transfer matrix to improve and optimize the gray system model (GM), which compensated for the gray model's lower prediction accuracy for time series with greater randomness and volatility, but poorly predicted nonlinear time series. Feng, Wei, and Guo (2012) established a high-speed railway subgrade settlement prediction model using least squares support vector machine (LS-SVM) with high

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prediction accuracy but poor prediction ability for large-scale data and complex data. Li, Li and Li (2017) used BP to predict shield tunnelling parameters under composite stratum conditions, with good prediction effect and good nonlinear mapping ability, but there were problems of easy overfitting and network parameters not easy to determine. Ding, Wei, and Gao (2023) used BP neural network optimized by genetic algorithm (GA) to predict soft soil subgrade settlement. The amount of subgrade settlement was accurately predicted, effectively solving the problem that BP is easy to overfitting, network parameters are not easy to determine, and the prediction accuracy was improved compared with BP. The combination of metaheuristics and BP can effectively solve the defects of BP, but there is still the problem of easy to fall into the local optimum, resulting in unstable model prediction. In order to solve this problem, some researchers had improved the metaheuristics. Zhuang, Zhang, and Xu (2012) improved the genetic algorithm (GA) by using selection operator and crossover and mutation operator and applied it to BP, which effectively solved the problem of BP easily falling into local optimum and the prediction effect was good. The SBOA algorithm is a new meta-heuristic algorithm proposed in 2024, which has stronger global search ability, simpler parameter setting, faster convergence speed and easy to combine with other algorithms compared with PSO algorithm and GA algorithm. SBOA algorithm combined with BP optimises the weights and thresholds of BP neural network, overcomes the problem of overfitting neural network, improves the convergence speed of the algorithm and enhances the stability of the model. model stability. Gray correlation analysis can achieve feature selection and dimensionality reduction, which enhances the interpretability of the model, reduces the risk of overfitting, and thus improves the prediction accuracy.

Therefore, aiming at the low prediction accuracy of high-speed railway subgrade settlement with a single model and without considering environmental influencing factors, this paper proposes a combined prediction model of gray relational analysis and SBOA-BP. Gray relational analysis (GRA) is used to analyse the atmospheric temperature and humidity, soil temperature and humidity collected by the sensors, and the influencing factors with strong correlation are used as inputs to the prediction model. Using a new type of meta-heuristic algorithm secretary bird optimisation algorithm (SBOA) to optimise the BP neural network (backpropagation neural network (BPNN)) to improve the prediction accuracy of the model, to construct the interval prediction model, and to provide guidance for the actual engineering and operation and maintenance, and to provide guidance for the highway engineering and operation and maintenance. and operation and maintenance, which provides a new reference for the prediction of high-speed railway subgrade settlement.

2. Access to data

The subgrade settlement data are actual settlement data measured by the railway department's engineering staff. In order to accurately obtain the data of factors affecting the railway subgrade settlement, the railway staff deployed atmospheric temperature and humidity sensors, soil temperature and humidity sensors in the historical settlement-prone areas. The data transmission module adopts 4G-LORA module, which uploads the data to the database in real time and displays them on mobile phones and Internet terminals. The structure of the high-speed railway subgrade temperature and humidity detection system is shown in Figure 1.

3. GRA-SBOA-BP model building

3.1 Gray relational analysis

Settlement of subgrade is usually affected by a variety of factors, in order to determine the strength of the influencing factors, this paper adopts the gray relational analysis (Liu & Li, 2017) to analyse the degree of correlation between the atmospheric temperature, humidity, soil temperature, humidity and other factors on the settlement of subgrade. The gray correlation analysis process is as follows (Zhu, Qi, & Li, 2024):

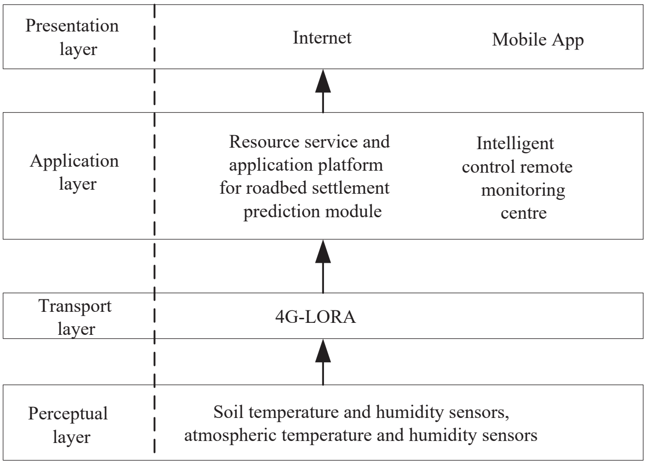

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Figure 1. Structure of temperature and humidity detection system for high-speed railway roadbed

(1) Establish the original parameter list. Assume that there are n-influencing factors and m-length feature sequences.

$$\left(x'_1, x'_2, \cdots, x'_n\right) = \begin{pmatrix} x'_1(1) & \cdots & x'_n(1) \\ \vdots & \ddots & \vdots \\ x'_1(m) & \cdots & x'_n(m) \end{pmatrix} \tag{1}$$

(2) Dimensionless calculations.

$$x_i(k) = \frac{x'_i(k)}{\frac{1}{m}\sum_{j=1}^{m} x'_i(j)} \tag{2}$$

where j, k = 1,2,. . ., m, the matrix after dimensionless quantisation is as follows:

$$(x_1, x_2, \cdots, x_n) = \begin{pmatrix} x_1(1) & \cdots & x_n(1) \\ \vdots & \ddots & \vdots \\ x_1(m) & \cdots & x_n(m) \end{pmatrix} \tag{3}$$

(3) Sequence difference calculation. The absolute values ($\Delta_i(k)$) corresponding to the reference and comparison sequences at each moment after the data are dimensionless, with the following formula:

$$\Delta_i(k) = |y(k) - x_i(k)| \tag{4}$$

(4) Correlation coefficient calculation.

$$\xi_i(k) = \frac{\min_i \min_j \Delta_i(k) + \rho \max_i \max_j \Delta_i(k)}{\Delta_i(k) + \rho \max_i \max_j \Delta_i(k)} \tag{5}$$

where $\min_i \min_j$ is the i-th comparison series, the j-th reference series of the smallest value; $\max_i \max_j$ is the i-th comparison series, the j-th reference series of the largest value. ρ is the resolution coefficient, generally take 0.5.

(5) Correlation calculation.

$$r_i = \sum_1^n w_k \xi_i(k) \tag{6}$$

where w_k is the entropy weight, when the correlation is greater than 0.65, it indicates a strong correlation; when the correlation is between 0.35 and 0.65, it indicates a moderate correlation; when the correlation is between 0 and 0.35, it indicates a weak correlation.

For the factors affecting the high-speed railway roadbed settlement proposed in this paper, the original data will be made gray correlation analysis, with the railway roadbed settlement as the parent sequence, the atmospheric temperature, atmospheric humidity, soil temperature, soil moisture as the subsequence, and the results of gray correlation calculations are shown in Table 1.

As can be seen from Table 1, the correlation coefficients of atmospheric temperature, atmospheric humidity, soil temperature and soil moisture are all greater than 0.65, indicating that these influencing factors are strongly correlated with railway roadbed settlement. Figure 2 shows the gray correlation coefficient diagram of atmospheric temperature, atmospheric humidity, soil temperature, soil moisture and settlement. From Figure 2, atmospheric humidity, soil humidity and settlement have the same increasing trend, which also shows that atmospheric humidity, soil humidity and settlement have a strong correlation. Therefore, the raw data of atmospheric temperature and humidity and soil temperature and humidity can be used as inputs to the model.

3.2 Secretary bird optimization algorithm

The secretary bird optimisation algorithm is mainly inspired by the secretary bird's survival behaviour in the natural environment, the algorithm is novel in its thinking and has obvious advantages over mainstream algorithms, and can be effectively applied to optimisation problems.

Table 1. Table of gray correlation coefficients

	Atmospheric temperature	Atmospheric humidity	Soil temperature	Soil humidity
Gray correlation	0.6880	0.8870	0.6556	0.7173
Gray correlation size ranking	3	1	4	2

Source(s): Authors' own work

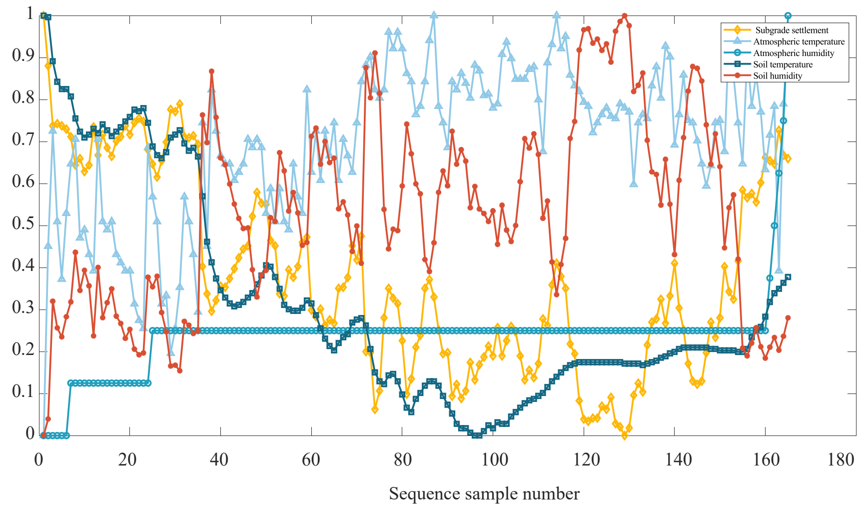

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Figure 2. Gray correlation coefficient map

3.2.1 Initialisation phase. The SBOA algorithm is a population-based meta-heuristic algorithm where each secretary bird is a member of the algorithm population. The secretary birds are randomly initialised in the initialisation phase with the following formula for the initialisation position:

$$X_{i,j} = lb_j + r \times \left(ub_j - lb_j\right), i = 1, 2, \ldots, N, j = 1, 2, \ldots, Dim \tag{7}$$

where X_i is the location of the i-th secretary bird, lb and ub are the lower and upper bounds of the population's range, and r is a 0–1 random number.

3.2.2 Exploration phase. Based on the duration of the secretary bird in the exploration phase, the whole exploration phase is divided into: $t < \frac{1}{3}T$ is the prey finding phase, $\frac{1}{3}T < t < \frac{2}{3}T$ is the prey consuming phase, and $\frac{2}{3}T < t < T$ is the prey attacking phase. t is the current iteration number and T is the maximum iteration number.

(1) Finding prey. The secretary bird introduces a differential evolutionary strategy in the prey finding phase, which can generate new strategies through the differences between individuals, thus enhancing the global search capability of the algorithm to avoid falling into local optimums. The position update formula for this phase is as follows:

$$X_{i,j}^{newP1} = X_{i,j} + \left(X_{random\_1} - X_{random\_2}\right) \times R_1 \tag{8}$$

where $X_{i,j}^{newP1}$ is the position of the j-th dimension i-th secretary bird in the new state, X_{random_1} and X_{random_2} are the random candidate solutions in this stage, and R_1 is a randomly generated dimension $1 \times Dim$ array in the interval [0,1].

(2) Consuming prey. After the secretary bird finds the prey, unlike other hunters who fight immediately, it mainly uses keen judgement and gradually hovers to provoke the prey, thus serving to consume the opponent's endurance. This stage mainly uses the historical best position and Brownian motion for location search. By using the historical best position to search around the neighbourhood, you can then find

the global optimal position faster. Brownian motion is introduced to use its randomness to enable individual secretary birds to explore the solution space more effectively and avoid falling into the local optimum to obtain better results. The position update formula for this phase is as follows:

$$X_{i,j}^{newP1} = X_{best} + \exp((t/T)\hat{}4) \times (RB - 0.5) \times \left(X_{best} - X_{i,j}\right) \tag{9}$$

where X_{best} is the historical best position and $RB = randn(1, Dim)$ is a randomly generated array of dimension $1 \times Dim$ from a standard normal distribution.

(3) Attacking prey. When the prey is exhausted, the secretary bird will find a suitable moment to attack immediately. The levy flight strategy is introduced in this phase to facilitate better global search and reduce the risk of the algorithm falling into local optimum. In order to better balance exploration and exploitation, a nonlinear convergence factor is introduced to improve the performance of the algorithm. The position update formula for this stage is as follows:

$$X_{i,j}^{newP1} = X_{best} + ((1 - t/T)\hat{}(2 \times t/T)) \times X_{i,j} \times RL \tag{10}$$

where $RL = 0.5 \times Levy(Dim)$, $Levy(Dim)$ are $Levy$-fighting distribution functions.

3.2.3 Development phase. In the first strategy, the secretary bird arrives near the predator and first adopts camouflage using the environment marking it as C_1. If there is no suitable camouflage environment, it chooses to fight or run away, marking the escape as C_2 . The location of this stage is updated as follows:

$$X_{i,j}^{newP2} = \begin{cases} C_1 : X_{best} + (2 \times RB - 1) \times (1 - t/T)^2 \times X_{i,j}, if\ rand < r_i \\ C_2 : X_{i,j} + R_2 \times \left(X_{random} - K \times X_{i,j}\right), else \end{cases} \tag{11}$$

3.3 SBOA algorithm performance test

3.3.1 Algorithm comparison and experimental parameter setting. In order to objectively evaluate the performance of the proposed meta-heuristic algorithms and verify the superior performance of the improved strategy of the SBOA algorithm, the performance of the SBOA algorithm is tested by selecting four standard test functions in the CEC-2022 test set. The SBOA algorithm is compared with the Gray Wolf Optimization Algorithm (GWO) (Mirjalili, Mirjalili, & Lewis, 2014), Whale Optimization Algorithm (WOA) (Mirjalili & Lewis, 2016), Dung Beetle Optimization Algorithm (DBO) (Xue & Shen, 2022), and Northern Goshawk Optimization Algorithm (NGO) (Dehghani, Hubálovský, & Trojovský, 2021), which have had superior performance in recent years. By comparing the worst value, optimal value, mean value and standard deviation of each algorithm on the test function, the first three can show the convergence speed and optimisation finding ability of the improved algorithms, and the standard deviation can determine the stability and reliability of the algorithms. In order to more accurately test the effectiveness of the SBOA algorithm and its comparative algorithms, the experiments were conducted using Windows 10 operating system and MATLAB R2022b as the programming software. All the algorithms were tested on the classical test function and set uniformly: the number of populations N = 30, the maximum number of iterations is 1,000, and each algorithm was run 30 times. As shown in Table 2, the parameters of these comparison algorithms were used as set in the original.

3.3.2 Algorithm development exploration analysis. As can be seen from Table 3, in the test, the worst value, the optimal value, the mean value and the standard deviation of the SBOA algorithm are closer to the theoretical optimal value, which reflects its strong search ability and high stability; in f1-f3, the SBOA algorithm's order of magnitude is lower than the other

Table 2. Comparison algorithm parameter settings

Algorithm	Parameter	Value
GWO	amin and amax	0 and 2
WOA	a	From 2 to 0
DBO	K and λ	0.1
	b	0.3
	s	0.5
SBOA/NGO	N	30

Source(s): Authors’ own work

Table 3. CEC-2022 experimental results

Function		SBOA	GWO	WOA	DBO	NGO
f1	Worst	1399.95	21414.23	66109.62	46153.00	8573.62
	Best	336.33	2975.41	10009.81	14210.72	3052.88
	Mean	675.10	13175.33	26279.59	23774.03	4791.89
	STD	320.78	4668.00	16041.58	9001.64	1683.63
f2	Worst	475.64	588.09	682.55	587.09	473.73
	Best	429.20	459.46	459.15	449.11	449.08
	Mean	456.83	505.34	578.86	493.64	456.21
	STD	15.59	45.33	75.82	40.79	11.31
f3	Worst	600.04	619.02	684.41	652.85	629.06
	Best	600.00	601.70	657.84	609.09	600.57
	Mean	600.02	606.88	668.63	635.71	609.79
	STD	0.01	5.73	8.87	13.49	8.67
f5	Worst	977.0319	1557.2075	6435.0057	2750.3329	1933.015
	Best	900.0895	956.8755	2225.0484	1056.1964	1175.8752
	Mean	914.1572	1211.5993	4081.8326	1838.3178	1534.7314
	STD	23.0222	203.55	1204.2058	523.1733	209.3676

Source(s): Authors’ own work

algorithms and its optimal value is much smaller than the optimal value of other algorithms, which demonstrates its excellent optimisation search ability. In f5, the SBOA algorithm has good balanced search and development ability.

3.3.3 Convergence analysis. In order to analyse the convergence speed, accuracy and ability to avoid local optimum of each algorithm, the convergence curves of each algorithm are shown in Figure 3. In f1-f3, the SBOA algorithm is much higher than other algorithms in both convergence speed and convergence accuracy, and the ability to avoid local optimum is stronger, and it converges to the optimal solution quickly; in f5, it can leave the local optimum earlier and achieve the global optimum, which shows that the SBOA algorithm has a good balance between global search and local development.

3.4 GRA-SBOA-BP based model

After the gray correlation analysis, the gray correlation of atmospheric temperature and humidity, soil temperature and humidity are all greater than 0.65, which proves that the four factors have a strong correlation with high-speed rail subgrade settlement, and can be used as inputs to the SBOA-BP prediction model. The original BP neural network has good prediction effect and strong nonlinear mapping ability, but it also suffers from the defects of being easy to overfitting and the network parameters are not easy to determine (Meng, Jiang, & Li, 2023). Some researchers have shown that the new meta-heuristic algorithm can effectively solve the

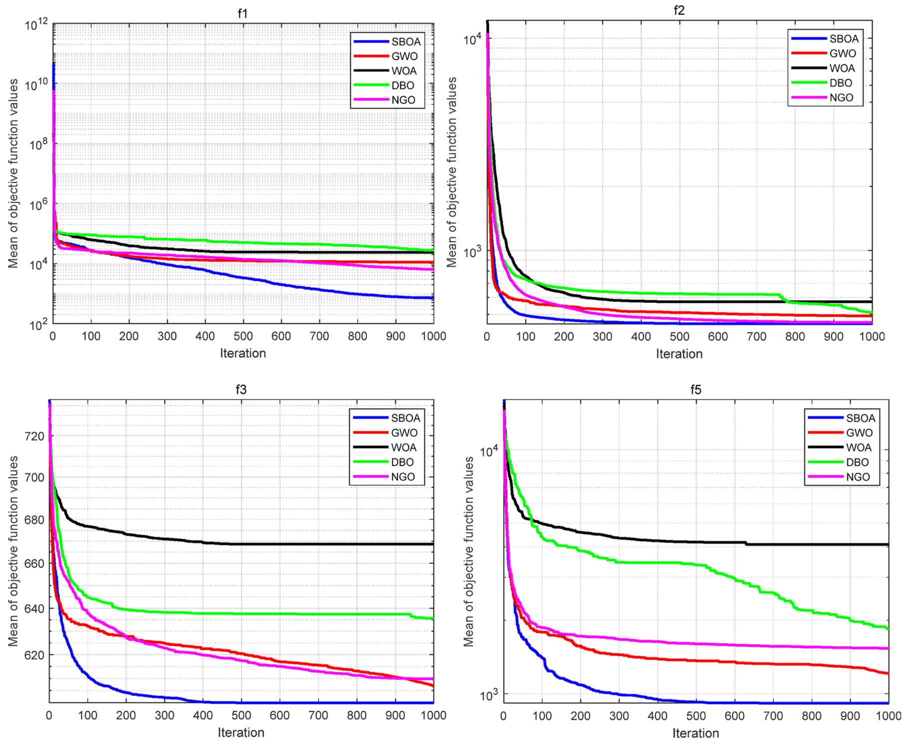

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Figure 3. Interval prediction results at different confidence levels

above defects of BP neural network. Therefore, in this paper, the new meta-heuristic algorithm Secretary Bird Optimisation Algorithm is used to optimise the BP neural network. The flowchart of the SBOA-BP algorithm is shown in Figure 4:

The overall process of the combined model is as follows:

(1) collect the data and do the pre-processing;

(2) use GRA to do the correlation analysis and get the main elements affecting the settlement of the subgrade;

(3) use main elements as the input of the SBOA-BP model to train the prediction model for the settlement of the roadbed and perform the settlement prediction;

(4) get the prediction interval for the settlement.

The parameters of SBOA algorithm are set as follows: number of populations N = 30. The parameters of BP neural network are set (Yu, Tian, & Wu, 2022), as follows: number of training times: 500, learning rate: 0.1, minimum error of training objective: 0.00001, standard BP neural network is used as a benchmark, and the number of nodes in the input, implicit, and output layers are set as 4–11–1.

Predictions can provide feasible recommendations for railway transport authorities in order to control the occurrence of diseases in advance, and the decision-making of railway authorities relies on high-quality prediction results. Therefore, in this paper, evaluation indexes such as MAE, RMSE, MAPE, and R^2 (Jian, Wan, & Jia, 2015) are used to judge the

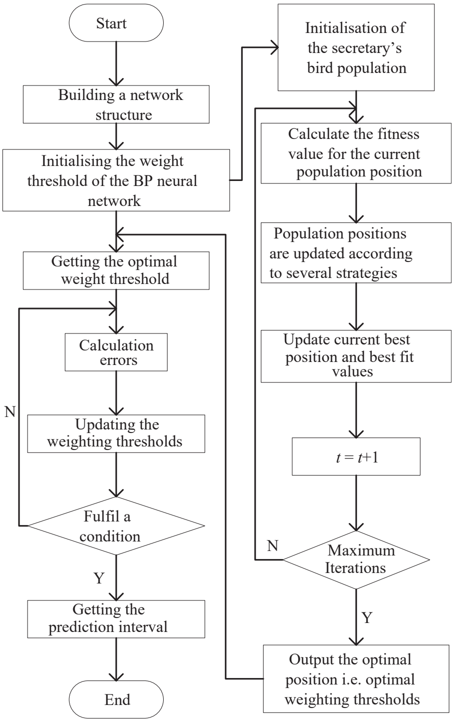

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Figure 4. Flowchart of SBOA-BP algorithm

accuracy and reliability of point prediction. In order to better evaluate the interval prediction results of the proposed scheme and the comparison scheme in this paper, PICP and PIAW are used to evaluate and analyse the reliability and accuracy of the interval prediction results (Wang, Ju, & Dong, 2024).

1) (Mean Absolute Error)

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|e_i| = \frac{1}{N}\sum_{i=1}^{N}\left|X_i^{observed} - X_i^{predicted}\right| \tag{12}$$

2) (Mean Square Error)

$$MSE = \frac{1}{N}\sqrt{\sum_{i=1}^{N}e_i^2} = \frac{1}{N}\sqrt{\sum_{i=1}^{N}\left(X_i^{observed} - X_i^{predicted}\right)^2} \tag{13}$$

3) (Root Mean Square Error)

$$RMSE = \sqrt{MSE} \tag{14}$$

4) (Mean Absolute Percent Error)

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{e_i}{X_i^{observed}}\right| \times 100\% = \frac{100}{N}\sum_{i=1}^{N}\left|\frac{X_i^{observed} - X_i^{predicted}}{X_i^{observed}}\right| \tag{15}$$

5) R^2

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(X_i^{predicted} - \overline{X_i^{observed}}\right)^2}{\sum_{i=1}^{N}\left(X_i^{observed} - \overline{X_i^{observed}}\right)^2} \tag{16}$$

In the above equation, N is the number of parameters, $X_i^{observed}$ is the observed value, $X_i^{predicted}$ is the predicted value, and e_i is the difference between the observed and predicted values.

6) interval coverage probability (PICP) refers to the probability that the real value of the settlement of high-speed railway subgrade is within the upper and lower boundaries of the interval, and the larger the value is, the more reliable and accurate the interval prediction model is.

$$PICP = \frac{1}{N}\sum_{n=1}^{N} S_n \tag{17}$$

7) The interval average width (PIAW) characterises the clarity of the model for interval prediction. At the same confidence level, the smaller the interval average width, the better the model interval prediction.

$$PIAW = \frac{1}{N}\sum_{n=1}^{N}\left(P_{\text{upper bound}} - P_{\text{lower bound}}\right) \tag{18}$$

where, N is the number of parameters, S_n is a Boolean function, and $P_{\text{upper bound}}$ and $P_{\text{lower bound}}$ are the upper and lower bounded settlement values predicted by the interval.

4. Experimental validation and analysis

In this paper, the experiment collects a total of 165 periods of data, of which the first 80% is used as the training set and the last 20% as the test set.

4.1 Comparison of different algorithmic models

Comparison experiments of BP model, SVM model and LSTM model are established respectively to verify that the BP model is adapted to the prediction of high-speed railway subgrade settlement. As can be seen from Figure 5, the overall prediction trend of the three models is consistent with the true value, and all of them deviate from the true value in the late stage of prediction, but the BP model is obviously closer to the true value. Combined with Table 4, the BP model has the smallest error and the largest R^2, which verifies that the BP model is adapted to the prediction of high-speed railway subgrade settlement.

From Figure 5, it can be seen that the BP model will have a large deviation in the late prediction stage, which may be caused by the BP neural network parameters not being the

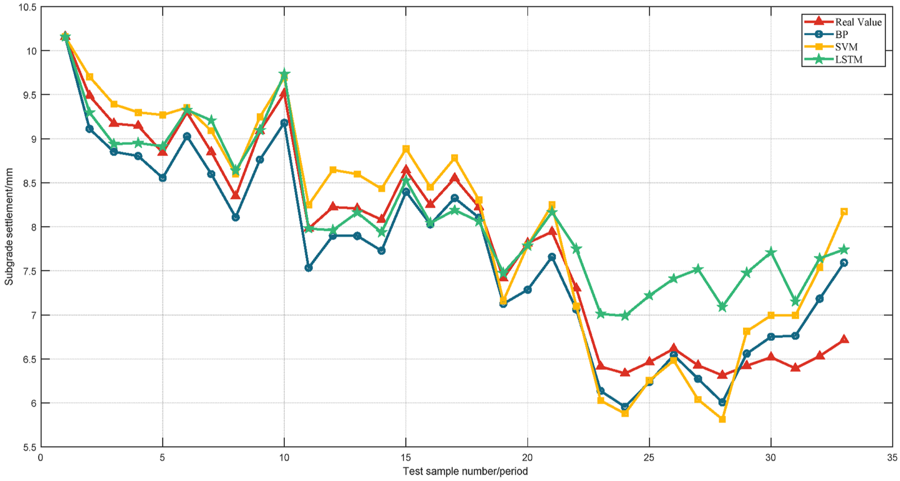

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Figure 5. Comparison of the predictive effects of different models

Table 4. Precision comparison of each model

Programme name	MAE/mm	RMSE/mm	MAPE/%	R^2
BP	*0.3039*	*0.3419*	*0.1389*	*0.8795*
SVM	0.3301	0.4288	0.1571	0.8104
LSTM	0.4086	0.5544	0.1603	0.6831

Source(s): Authors' own work

optimal parameters or overfitting. In order to improve the model's late fitting effect and overall prediction accuracy the new meta-heuristic algorithm SBOA algorithm is introduced to optimise the BP neural network.

4.2 Comparative experiments of different algorithms to optimise the BP model

In order to verify the superiority of the optimised BP model of the SBOA algorithm, comparative experiments of the BP model, GWO-BP model, WOA-BP model, DBO-BP model, NGO-BP model and SBOA-BP model are established.

As can be seen from Figure 6, all the optimisation algorithms optimise the BP model closer to the real value than the single BP model, especially the SBOA-BP model is closer to the real value in the late stage of prediction, combined with Table 5, the SBOA-BP model has the smallest error and the largest R^2; the BP model has the largest error and the smallest R^2. The superiority of the SBOA algorithm can be seen, which moreover indicates that the SBOA-BP model has high prediction accuracy, stability and reliability (see Figure 7).

Point prediction results have obvious disadvantages in dealing with uncertainty, risk assessment and decision support, in order to improve such situations, this paper constructs an interval prediction model, in order to assess the effect of interval prediction, 80%, 90% confidence level as an example. The following figure shows the interval prediction effect.

Overall, all models cover most of the true values, indicating that all models possess good wraparound and coverage, verifying that the models are adapted to interval prediction.

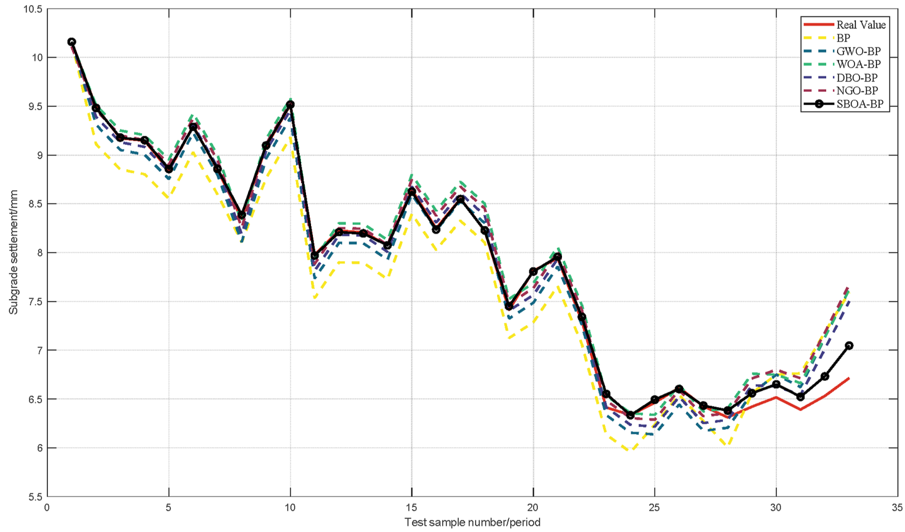

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Figure 6. Comparison of the effect of different models to optimise BP

Table 5. Comparison of BP prediction accuracy of different algorithms for optimisation

Programme name	MAE/mm	RMSE/mm	MAPE/%	R^2
BP	0.3039	0.3419	0.1389	0.8795
GWO-BP	0.1733	0.2447	0.0235	0.9546
WOA-BP	0.1540	0.2329	0.0202	0.9589
DBO-BP	0.1156	0.1922	0.0158	0.9720
NGO-BP	0.1391	0.2364	0.0186	0.9576
SBOA-BP	*0.0448*	*0.0848*	*0.0065*	*0.9805*

Source(s): Authors' own work

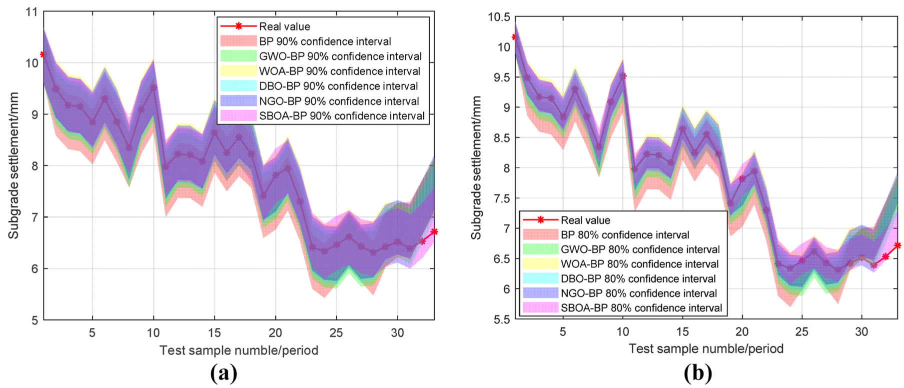

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Figure 7. Interval prediction results at different confidence levels (a) (b)

Table 6. Evaluation results of interval prediction at different confidence levels

Programme name	90% confidence level PIAW/mm	PICP/%	80% confidence level PIAW/mm	PICP/%
BP	1.0498	0.91	0.5072	0.82
GWO-BP	1.0307	0.94	0.4833	0.88
WOA-BP	1.0307	0.94	0.4942	0.85
DBO-BP	1.0236	0.97	0.4601	0.94
NGO-BP	1.0307	0.94	0.4942	0.85
SBOA-BP	*1.0100*	*1*	*0.4518*	*0.97*

Source(s): Authors' own work

Combined with Table 6, the interval coverage of all models exceeds the confidence level, indicating that the models obtain effective prediction intervals.The SBOA-BP model has the largest interval coverage under two confidence levels, indicating that the model is more reliable; the average width of the intervals of the SBOA-BP model is smaller under the same confidence level, indicating that the predicted values of the model are closer to the true values. In summary, the superiority of SBOA-BP model in interval prediction is verified.

5. Summary

In this paper, a gray correlation analysis and SBOA algorithm optimization BP neural network of high-speed railway subgrade settlement interval prediction method is proposed, which improves the accuracy of settlement prediction and is of guiding significance for practical engineering applications. The following conclusions are obtained:

(1) Sensors are buried in the historical settlement-prone area, and gray correlation analysis is used to verify that atmospheric temperature and humidity, and soil temperature and humidity have correlation on the settlement of high-speed railway subgrade;

(2) The SBOA algorithm is used to optimize the BP neural network to get the optimal weights and thresholds, which improves the prediction accuracy of the model;

(3) Under a given confidence level, the successful prediction of the settlement of the roadbed is achieved. fluctuation range at a given confidence level, which makes it more widely used in engineering practice.

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