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Application of Simulated Annealing Optimization Model in Foundation Settlement Prediction

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Abstract. Reasonable prediction of foundation settlement is of great significance to saving construction cost, ensuring construction quality and ensuring the safety of construction process.In neural network to reduce the error of gradient descent, easy to fall into local optimum and higher requirements for the number of original data and shortcomings of simulated annealing optimization model is put forward, realize the prediction of finding the global optimal and focus on the time delay neural network are optimized by the coordination factor (FTDNN) and nonlinear regression neural network (NARNN) the accuracy of the two models, Improve the prediction error caused by insufficient original data.The results show that the accuracy of the simulated annealing optimized prediction model is significantly higher than that of the two neural networks alone, which has certain engineering significance.

Keywords. Simulated annealing, Neural network;Foundation settlement, Prediction model.

1. Introduction

If the foundation settlement can not be predicted accurately, the building may fail to fulfill its specific function and even collapse. At present, there are three prediction methods for foundation settlement: numerical analysis, numerical calculation and theoretical calculation.In the theoretical calculation method, it is assumed that the soil only deforms in the vertical direction, while there is no deformation in the lateral direction, which will lead to a smaller calculation result than the actual value[1]. The parameters of finite element, finite difference and other numerical simulation methods are difficult to determine, and it is not easy for engineers to grasp quickly[2-3]. For saturated soft soil, fitting curve method is more commonly used.However, the measured data show that the settlement amount obtained by exponential curve method is usually small and not suitable for long-term prediction. The results of hyperbolic prediction are often small in the later period and the accuracy of short-term settlement prediction is low[4-7]. Wu Ruihai[8]Compared with the standard particle swarm optimization algorithm, it is proved that the improved algorithm has better global search ability.Dong Qin bright[9] Combined with simulated annealing method and Biot consolidation theory, the advantages of the two methods are integrated to predict the

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settlement of the foundation, which provides experience for the prediction of the settlement of the foundation compacted by riprap.NiuShun raw[10]. The simulated annealing method is used to optimize the algorithm for long and short pile composite foundation, and an example is given to prove the accuracy and accuracy of the scheme. Xu Xinyue[11]. Artificial settlement network is established and genetic algorithm is used to predict the settlement of soft soil foundation to reduce the uncertainty and improve the prediction accuracy. In this paper, an optimization prediction method based on FTDNN and NARNN is established by using simulated annealing method and coordination factor thinking to predict the settlement of engineering foundation.

2. Foundation Settlement Prediction Method Based on Dynamic Neural Network

2.1. Focused Time-delay Neural Network (FTDNN)

Time delay neural network (TDNN) was Waibel in 1989[12]. It is used to solve the problem that the hidden Markov model cannot adapt to the dynamic time domain change of speech signal.Neural network consists of three clusters, including input layer, output layer and hidden layer.A tap delay line (TDL) is added to the input end of THE TDNN feed-forward network to become the dynamic neural network FTDNN. FTDNN network is especially suitable for the application of time series prediction, because TDL only appears at the input end, it does not need to calculate the gradient by the method of dynamic back propagation, so the training speed of FTDNN network is faster than other dynamic networks.

2.2. Nonlinear Autoregressive Neural Network (NARNN)

Quantile Regressive neural Network (QRNN) was proposed by Taylor in 2000.Neural network regression is composed of two aspects, divided into neural network and regression, has a powerful function.Not only can the whole conditional distribution of response variables be revealed, but also the nonlinear characteristics of the system can be simulated.

Nonlinear autoregressive neural network (NARNN) is a kind of dynamic neural network composed of static neurons and network output feedback.Different from FTDNN network, NARNN network uses its own data for regression calculation, which belongs to unsupervised learning.

3. Simulated Annealing Coordination Factor Optimization

The more multi-layer sensing neurons, the larger the corresponding weight matrix, the higher the degree of freedom, the more output, the more complex the model, the more powerful the model.However, the more variables, the more error surfaces, which leads to the gradient descent method easily fall into the local minimum and stop the search.Simulated annealing algorithm[13] is an effective algorithm to solve the local minimum energy. Its basic idea is to simulate the metal annealing process, that is, the object is heated to high temperature first, so that the object has a higher internal energy;Then, it slowly cools down, and as it cools down, it slows down.During the simulated annealing, the object was subjected to a horizontal sloshing effect, which made the object jump out from any local minimum. This horizontal sloshing intensity was moderate, from strong to weak, and finally made the object have the ability of global search optimization.

Then the global optimal solution of the objective function is searched randomly in the solution space by using the probabilistic jump property in simulated annealing.The whole process is divided into three stages: heating, isothermal and cooling.During this period, the internal energy decreases continuously, and finally reaches the minimum internal energy, that is, the optimal solution is obtained.If the new solution is better than the current one, the new solution is accepted; otherwise, the Metropolis criterion is used to determine whether to accept the new solution.The acceptance probability is:

$$p = \begin{cases} 1, r_{xnew} >= r_{xold} \\ exp(\frac{r_{xnew}-r_{xold}}{q*t}) \ , \ r_{xnew} < r_{xold} \end{cases} \quad (1)$$

Where, r is the objective function, then rxnewIs the result of the new solution, rxoldIs the calculation result corresponding to the current solution.Q is the cooling rate and T is the temperature.If you compute rxnewIs better than that of rxold, the new solution is taken as the current optimal solution.If you calculate rxnewBelow the rxold, the new solution will be selected with a certain probability, and the selected probability value is exp((rxnew-rxold)/q * t).

The results of the two neural networks were weighted by simulated annealing optimization coordination factor to integrate the advantages of the two neural networks and make the optimized results more accurate.The coordination factors are x, y, x+y=1, x, y≥0.

4. Case Analysis

4.1. Project Overview

Chang Run Xiang Heyuan 8# residential building is located in Liaocheng Dongchang Road north, west of the Duhaihe.The strata are mainly silty clay and silty clay. The first observation date is December 10, 2012, and the deadline is August 31, 2014. Point J84 was well preserved during the observation and was located at the midpoint of the long edge of the building.Monitoring data are shown in table 1.

Table 1. Settlement data at point 8# J84 of Changgrun Xiangheyuan

Time /d	Settlement /mm	Time /d	Settlement /mm	Time /d	Settlement /mm	Time /d	Settlement /mm
0	0.00	128	29.85	232	37.09	305	39.43
11	0.72	140	31.43	252	37.71	334	39.57
23	2.98	157	33.23	257	37.88	486	39.58
26	3.83	168	34.15	261	38.06	640	39.69
39	7.56	181	35.04	268	38.59		
57	13.31	194	35.75	275	39.17		
112	24.24	209	36.31	286	39.30		

4.2. Data Preprocessing

Spline interpolation method was used to obtain the settlement value with a time interval of 30d. The settlement data are shown in table 2.

Table 2. Settlement data at 8# J84 point in Changgrun Xiangheyuan with an interval of 30d.

Time/ d	Accumulated settlement /mm	Time /d	Accumulated settlement /mm	Time /d	Accumulated settlement /mm
30	4.98	240	37.40	450	39.58
60	13.91	270	38.76	480	39.58
90	19.87	300	39.40	510	39.60
120	27.05	330	39.55	540	39.62
150	32.49	360	39.57	570	39.64
180	34.97	390	39.57	600	39.66
210	36.34	420	39.58	630	39.68

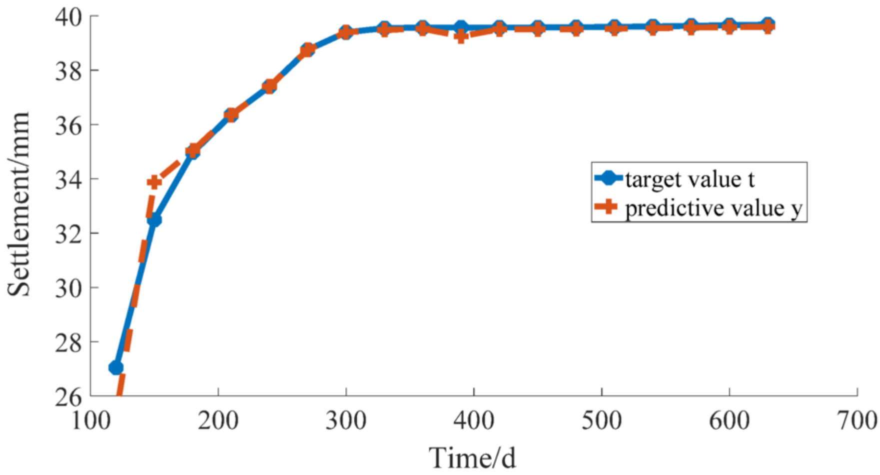
4.3. Comparison of Different Prediction Methods

FTDNN and NARNN neural network time series prediction methods are used to predict foundation settlement. The parameters of each method are consistent, the delay is 1:3, and no data grouping is carried out. There is 1 hidden layer and 10 neurons in the hidden layer.

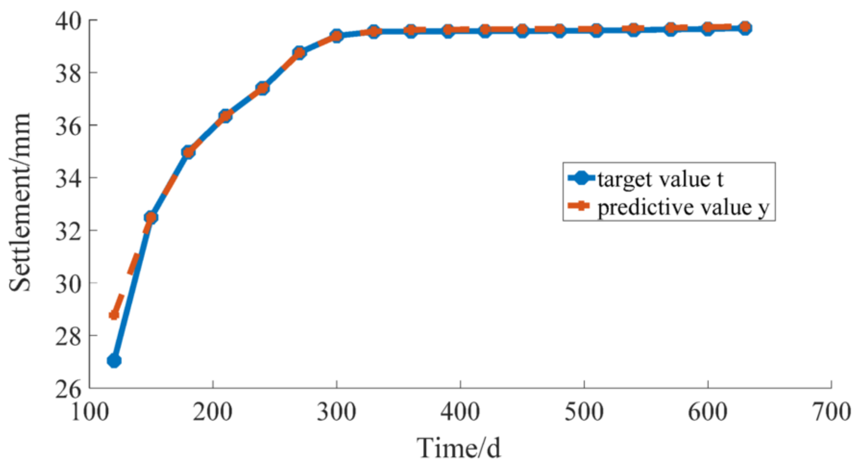
The prediction results of the two methods are shown in table 3, as shown in the comparison curve 1, where T is the target value and Y is the predicted value.

Table 3. Prediction results of foundation settlement by FTDNN and NARNN neural network

Time/d	FTDNN Predicted settlement /mm	NARNN Predicted settlement /mm	Time/d	FTDNN Predicted settlement /mm	NARNN Predicted settlement /mm
120	25.3157	28.7749	390	39.2508	39.6368
150	33.877	32.4934	420	39.5113	39.6458
180	35.0425	34.9511	450	39.5109	39.6507
210	36.3459	36.3422	480	39.5126	39.6527
240	37.4016	37.3999	510	39.5297	39.6549
270	38.754	38.7553	540	39.5477	39.6845
300	39.3997	39.3915	570	39.5681	39.708
330	39.4881	39.5622	600	39.5859	39.7303
360	39.5298	39.6239	630	39.6046	39.7531



(a) FTDNN network prediction results



(b) NARNN network prediction results

Figure 1. Comparison of prediction results between the two methods

Table 3 shows the prediction results of foundation settlement by FTDNN and NARNN neural network.Compared with figure 1 (a) and (b), the accumulated settlement of FTDNN network after 120 days is significantly different from the target value, and the accumulated settlement of NARNN network before 150 days is significantly different from the target value.

The difference between the two methods is large at different times, so this paper uses the coordination factor to integrate the advantages of the two methods at different times to achieve more accurate prediction results. Firstly, the optimal X value is selected, the initial temperature is set as 100, the lowest temperature is 0.01, the cooling rate is 0.99, and the maximum iteration number is 100. After calculation, the optimal coordination factor X value can be obtained.Secondly, according to x+y=1, the optimal coordination factor y value can be selected.The final coordination factor is determined according to the above initial value. The coordination factor of FTDNN network is 0.414648962, and that of NARNN network is 0.585351038.The final prediction results are shown in table 4. The comparison curve is shown in figure 2.

Table 4. Prediction results of optimized foundation settlement by simulated annealing method

Time/d	Simulated annealing optimized predicted settlement / mm	Time/d	Simulated annealing optimized predicted settlement /mm	Time/d	Simulated annealing optimized predicted settlement /mm
120	27.3404	300	39.3949	480	39.5946
150	33.0671	330	39.5315	510	39.6030
180	34.9890	360	39.5849	540	39.6278
210	36.3437	390	39.5887	570	39.6496
240	37.4006	420	39.5900	600	39.6704
270	38.7548	450	39.5927	630	39.6915

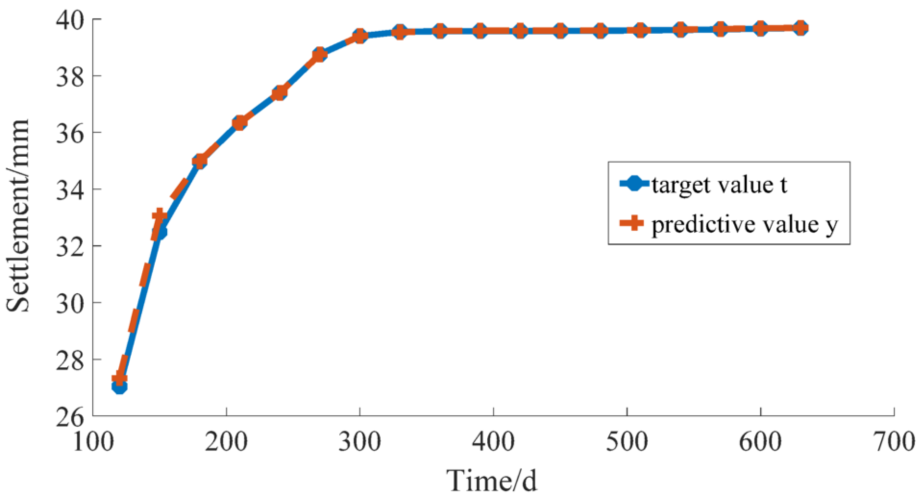


Figure 2. Optimization prediction results of simulated annealing method

The fitting precision of the three methods is compared with the minimum mean square error and maximum correlation degree. The comparison results are shown in table 5.

Table 5. Comparison of fitting accuracy of prediction methods

Neural network model	Mean square error (mse)	Maximum correlation
FTDNN	0.0775	0.8692
NARNN	0.0968	0.9209
Simulated annealing optimization model	0.0362	0.9540

As shown in table 5, the minimum mean square error and maximum correlation degree of simulated annealing are superior to those of the two neural networks.

5. Conclusion

The accumulated settlement of FTDNN network after 120 days differs greatly from the target value, and the accumulated settlement of NARNN network before 150 days differs greatly from the target value.The prediction results of the two methods differ greatly from the target value at different time. The simulated annealing method is used to prevent the neural network from falling into the local minimum value and the coordination factor is used to synthesize the advantages of the two neural networks, so the prediction accuracy is improved obviously.

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