E3S Web of Conferences 248, 03065 (2021) https://doi.org/10.1051/e3sconf/202124803065
CAES 2021

Research on Settlement Prediction of Small Water Conservancy Project based on ELM Model Optimized by Genetic Algorithm

Ruizi Yang[1,*]

[1] Management Science and Engineering, School of management, Tianjin University of Technology, China

Abstract. To find suitable for small water conservancy engineering standard method for prediction of subsidence. This paper based on the genetic algorithm GA optimization extreme learning machine, three different ELM model activation function. From this, six computational models are obtained. According to the input of groundwater dynamic changes, precipitation, temperature and soil four indicators of the two kinds of input combinations, a total of 12 kinds of model input. It's concluded that the optimal settlement prediction model, the results showed that: Ga-ELM_{sin} model shows high accuracy, and genetic algorithm can improve the calculation accuracy of ELM model. Groundwater dynamics is the main factor affecting settlement.

1 Introduction

With the growth of the domestic population and the rapid development of the economy, the requirements for the quality of the project are also gradually improved in the limited land resources. It is the focus of relevant industries to promote engineering development and improve residents' quality of life[1-2]. Small water conservancy projects are closely related to the life of residents. China's water conservancy industry is mainly concentrated in the construction of small water conservancy projects, which have direct and obvious benefits and are directly related to residents' daily life and water use for crops, and are of great significance to the improvement of residents' life[3-4]. The quality and operation management of small water conservancy projects may directly affect the daily work and life of residents. However, due to the small water conservancy projects' less investment and remote location, the implementation degree of project quality monitoring is low, which seriously affects their service life.

Settlement is one of the main reasons that affect the service life and durability of a project. The settlement is mainly affected by natural factors and human factors, resulting in deformation in the area where the project is located and resulting in certain damage to the main structure of the project due to additional stress[5].Long-term settlement observation shows that there is a certain distribution law in the process from the construction period to the stable period, but the settlement is not easy to be discovered and has a long periodicity, which has become an important geological disaster and has been listed as the focus of prevention and observation[6].

With the increasingly serious influence of settlement, it has become the research of relevant departments to find out the reasonable settlement prediction method while observing the settlement daily. Among them, the machine learning neural network model is widely used. Wang Lu and Gui Zhanfei[7] established a building settlement prediction model based on *GM-ARMA-BP* model, and pointed out that this combined model overcame the disadvantages of the single model. By integrating the advantages of each model, the prediction accuracy of the comprehensive model was improved by at least 50% compared with that of the single model. Feng Shaoquan et al.[8] established a prediction model for the settlement amount of elevated bridge piers based on the combined model of *GA-BP-MC*, and proved the scientific nature of the model based on the index of absolute error and relative error. Song Chuping[9] also established the settlement prediction model of deep foundation pit based on the improved BP neural network model, and pointed out that the improved BP neural network model had faster convergence speed and higher generalization ability. Peng Yuan[10] used genetic algorithm to optimize BP neural network model to predict the settlement of buildings, and achieved good results.

Extreme learning machine (*ELM*) is a new neural network algorithm. This algorithm overcomes the shortcoming of slow convergence speed of traditional BP neural network model and is applied to data training and prediction. The genetic algorithm facilitates the model to find the optimal path and find out the rules of training data. In this paper, a settlement prediction model for small water conservancy projects is established based on the ultimate learning machine (*GA-ELM*) algorithm of genetic optimization.

2 Research methods

2.1. Extreme learning machine model (*ELM*)

Ultimate Learning machine model (*ELM*) is a single-hidden layer feedforward algorithm model, which is

* Corresponding author: ruiz193144302@stud.tjut.edu.cn

https://doi.org/10.1051/e3sconf/202124803065

mainly composed of input layer, hidden layer and output layer. Its basic structure is shown in Figure 1.

Let the activation function of hidden layer neurons be $g\ (\omega,\ X,\ b)$, then the expression of output layer of *ELM* model is:

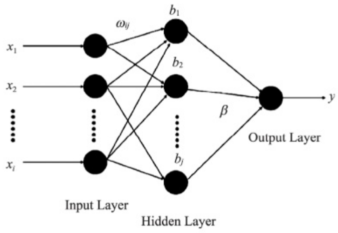

Fig. 1. *ELM* model basic structure.

$$F(X_i) = \sum_{j=1}^{m} \beta_j g(\omega_{ij} X_i + b_j) \tag{1}$$

Where β_j - the connection value between the hidden layer and the output layer; ω_{ij} - the connection value between the input layer and the hidden layer; X_i - Input layer variable value; b_j - threshold for the JTH hidden layer.

The activation function of *ELM* model can be divided into three types: Sine function, Radbas function and Hardlim function. In this paper, three activation functions are respectively used to establish the settlement prediction model for small water conservancy projects. The specific formulas of the three functions are as follows:

Sine function ELM_{sin}:

$$g(\omega_{ij}, X_i, b_j) = g(\omega_{ij}, X_i + b_j) = sin(\omega_{ij}, X_i + b_j) \tag{2}$$

Radbas function ELM_{rad}:

$$g(\omega_{ij}, X_i, b_j) = \exp\ \left(-\frac{||X-\omega_{ij}||^2}{b_j^2} \right) \tag{3}$$

Hardlim function ELM_{hard}:

$$g(\omega_{ij}, X_i, b_j) = \begin{cases} 1, & \omega_{ij} X + b_j \geq 0 \\ 2, & \omega_{ij} X + b_j < 0 \end{cases} \tag{4}$$

2.2. Genetic algorithm optimization of extreme learning machine model (*GA-ELM*)

The application of the principle of genetic algorithm in the optimization of neural network learning can help the neural network model find the optimal solution as soon as possible and shorten the training time of the model. The specific steps for *ELM* model optimization are as follows: determine the *ELM* calculation structure and determine the length of the model calculation based on the original number of settlement data; Based on genetic algorithm, the fitness value of each subsidence data individual is calculated to find the optimal solution. Finally, the *GA-ELM* model is determined and the predicted data is obtained. The specific steps are shown in Figure 2.

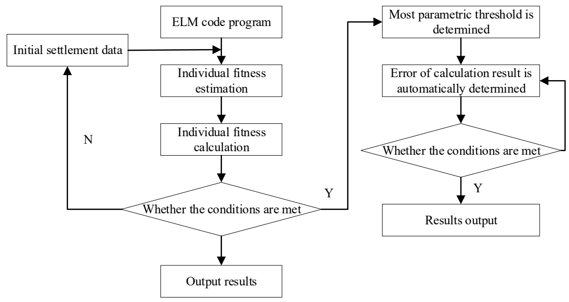

Fig.2. *Ga-ELM* model calculation steps.

2.3. Model training and validation

The subsidence of a small water conservancy project is mainly related to the groundwater dynamics, precipitation, air temperature and soil quality changes of the project site. The dynamic of groundwater is the main factor that affects the settlement of projects. Three activation function of the genetic algorithm to optimize the *ELM* model, based on four kinds of influence factors of 2 kinds of combinations: 1 enter groundwater dynamic combination, precipitation, temperature and soil changes in four indicators, combination of two input precipitation, temperature and soil changes in three kinds of index, specific combination forms are shown in table 1, we validate the calculation precision of different models under different input methods.

Table 1. Model parameter input.

Model	Input parameters	Model code
1. GA-ELM_{sin}	Groundwater dynamics, precipitation, air temperature and soil quality	ELM_1
2. GA-ELM_{rad}		ELM_2
3. GA-ELM_{hard}		ELM_3
4.ELM_{sin}		ELM_4
5. ELM_{rad}		ELM_5
6. ELM_{hard}		ELM_6
7. GA-ELM_{sin}	Changes in precipitation, air temperature and soil quality	ELM_7
8. GA-ELM_{rad}		ELM_8
9. GA-ELM_{hard}		ELM_9
10.ELM_{sin}		ELM_{10}
11. ELM_{rad}		ELM_{11}
12. ELM_{hard}		ELM_{12}

2.4. Model accuracy verification

Take root mean square error (*RMSE*), relative root mean square error (*RRMSE*), determination coefficient (R^2), model efficiency coefficient (E_{ns}) and average absolute error (*MAE*) as the model accuracy evaluation index system, and the specific formula is as follows:

$$RMSE = \sqrt{\frac{1}{m} \sum_{i=1}^{m} (Y_i - X_i)^2 \times 100\%} \tag{5}$$

$$RRMSE = \frac{\sqrt{\frac{1}{m} \sum_{i=1}^{m} (Y_i - X_i)^2}}{\bar{X}} \times 100\% \tag{6}$$

$$R^2 = \frac{[\sum_{i=1}^{m} (X_i - \bar{X})(Y_i - \bar{Y})]^2}{\sum_{i=1}^{m} (X_i - \bar{X})^2 \sum_{i=1}^{m} (Y_i - \bar{y})^2} \tag{7}$$

$$MAE = \frac{1}{m} \sum_{i=1}^{m} |Y_i - X_i| \tag{8}$$

 https://doi.org/10.1051/e3sconf/202124803065

$$E_{ns} = 1 - \frac{\sum_{i=1}^{m}(Y_i - X_i)^2}{\sum_{i=1}^{m}(X_i - \bar{X})^2} \qquad (9)$$

Where, Y_i - different methods to process values; X_i - the measured standard value; The average of $\bar{X}$ − X_i; *m*- Number of data samples.

GPI index is introduced to comprehensively judge the accuracy of different models. The specific formula is as follows:

$$GPI = \sum_{j=1}^{5} \alpha_j (g_j - y_{ij}) \qquad (10)$$

Where, α_j - constant; *MAE* and *RRMSE* are 1, *NS* is − 1; g_j - the median of the scaling values of different indicators; Y_{ij} - the scale values of different indicators.

3 Results and analysis

3.1. Comparison of settlement fitting effect between different models

Comparison and analysis of settlement prediction results and measured values by different models are shown in Figure 3. As can be seen from Figure 3, the simulation accuracy of different prediction models is different, but the overall data change trend is basically consistent with the measured value change trend. The settlement value of different parts of the building is different, the settlement value of the edge of the building is higher than that of the inside of the building. The ELM_1 model performs well in the prediction of building edge and internal settlement, with the simulated value closest to the measured value, while the ELM_{12} model has the worst fitting effect.

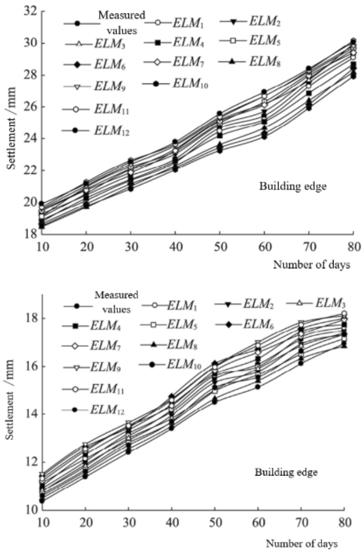

Fig. 3. Comparison of fitting effect between different model settlement prediction and measured value

3.2. Comparison of settlement prediction accuracy of different models

The accuracy of the prediction results of different models is shown in Table 2. As can be seen from Table 2, there are certain differences in the accuracy indexes of different models, and the accuracy of models at different positions is different. At the edge of the building, The Precision of ELM_1 model is the highest, and the values of *RMSE*, *RRMSE*, R^2, *ENS* and *MAE* are 1.719mm, 12.7%, 0.964, 0.946 and 1.283mm respectively. The model has the lowest error and the highest consistency with the measured value, while the precision of ELM_{12} model is the lowest. The values of *RMSE*, *RRMSE*, R^2, E_{NS} and *MAE* were 3.398mm, 25.0%, 0.803, 0.789 and 2.524mm, respectively, with the highest error and poor consistency.

Inside the building, the ELM_1 model also has the highest precision, while the ELM_{12} model has the lowest precision. The values of *RMSE*, *RRMSE*, R^2, E_{ns} and *MAE* can be divided into 1.245 and 3.471mm, 9.1% and 25.5%, 0.974 and 0.795, 0.973 and 0.793, 0.844 and 2.403mm. The accuracy of the 3 activation functions of *ELM* model is sine function > Radbas function > Hardlim function. The accuracy of the *ELM* function optimized by genetic algorithm is generally higher than that of the unoptimized *ELM* model under the same activation function. At the same time, when the dynamic influence factors of groundwater are taken into account, the precision of the model can be significantly improved, *RMSE* can be reduced by at least 15.6%, *RRMSE* by at least 20.4%, R2 by at least 22.6%, *ENS* by at least 18.7% and *MAE* by at least 21.8%.

Table 2. Comparison of precision indexes of different models

Measuring point	Precision index	ELM_1	ELM_2	ELM_3	ELM_4
Edge	*RMSE*/mm	1.719	1.797	2.033	2.149
	RRMSE/%	12.7	13.2	15.0	15.8
	R^2	0.964	0.96	0.948	0.941
	E_{NS}	0.946	0.941	0.925	0.916
	MAE/mm	1.283	1.353	1.525	1.604
Internal	*RMSE*/mm	1.245	1.410	1.543	1.610
	RRMSE/%	9.1	10.4	11.3	11.8
	R^2	0.974	0.966	0.959	0.945
	E_{NS}	0.973	0.966	0.959	0.956
	MAE/mm	0.844	0.945	1.072	1.077
Measuring point	**Precision index**	**ELM_5**	**ELM_6**	**ELM_7**	**ELM_8**
Edge	*RMSE*/mm	2.161	2.397	2.406	2.700
	RRMSE/%	15.9	18.4	17.7	19.9
	R^2	0.942	0.923	0.929	0.924
	E_{NS}	0.915	0.886	0.894	0.867
	MAE/mm	1.632	1.869	1.798	2.108
Internal	*RMSE*/mm	1.538	1.830	1.760	1.869
	RRMSE/%	11.3	13.4	12.9	13.7
	R^2	0.96	0.943	0.947	0.941
	E_{NS}	0.956	0.943	0.947	0.94
	MAE/mm	1.067	1.256	1.183	1.271
Measuring point	**Precision index**	**ELM_9**	**ELM_{10}**	**ELM_{11}**	**ELM_{12}**
Edge	*RMSE*/mm	2.809	2.9	3.068	3.398
	RRMSE/%	20.7	21.4	22.6	25.0
	R^2	0.914	0.904	0.842	0.803
	E_{NS}	0.856	0.847	0.828	0.789
	MAE/mm	2.165	2.237	2.305	2.524
Internal	*RMSE*/mm	1.982	2.049	3.157	3.471
	RRMSE/%	14.6	15.1	23.2	25.5
	R^2	0.934	0.929	0.835	0.795
	E_{NS}	0.933	0.928	0.829	0.793
	MAE/mm	1.377	1.427	2.211	2.403

3.3. Comparison of *GPI* index of settlement prediction by different models

Figure 4 shows the *GPI* index comparison of the prediction results of different models. It can be seen from

 https://doi.org/10.1051/e3sconf/202124803065

the figure that *GPI* is calculated from the simulation results of different models *GPI* is different at different locations. At the edge of the building, ELM_1 model has the highest *GPI* (1.904), while ELM_{12} model has the lowest accuracy (−3.096). Inside the building, ELM_1 model has the highest accuracy, ELM_{12} model has the lowest accuracy, and *GPI* is 1.052 and −3.948. In summary, $GA\text{-}ELM_{sin}$ model is the model with the highest accuracy for settlement prediction of small water conservation projects.

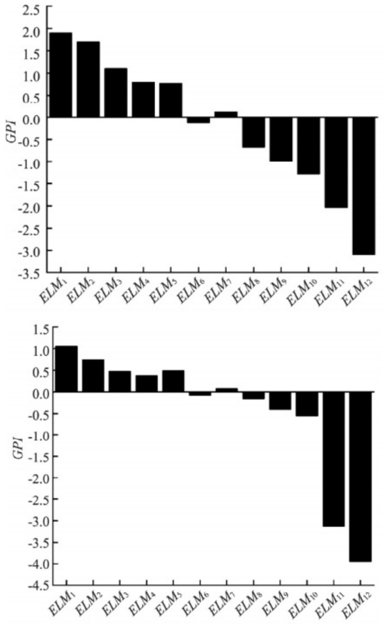

Fig. 4. Comparison of *GPI* index of settlement prediction by different models (the top is the edge, the bottom is the inside)

4 Conclusion

Based on the limit learning machine model, this paper studies the settlement prediction models of small water conservancy projects under different models. Based on the three activation functions of ELM model, genetic algorithm was used to optimize each model respectively. And the calculated value was compared with the measured value. The conclusion was drawn: although there were some differences in the accuracy of different models, the predicted value was basically consistent with the change trend of the measured value. The calculation accuracy of *ELM* model can be improved by genetic algorithm. Among the 3 activation functions of *ELM* model, sine activation function has the highest accuracy. In summary, $GA\text{-}ELM_{sin}$ model can be the standard model for settlement prediction of small water conservancy projects. In the future research, the model can be compared with the generalized regression neural network model and BP neural network model to further illustrate the scientific nature of the model.

References

1. Liu Yitao. Development of BIM Technology and its Application in Water Conservancy Projects [J].*Water Planning and Design*, 10 (2019)
2. Zhang Weidong. Countermeasures and Suggestions for the development of Foreign Projects in China's Water Conservancy and hydropower Industry [J].*Water Resources Planning and Design*, 1 (2009)
3. Huangfu Mingxia, WANG Wenting, LIU Yuqing. Quality control measures for construction of small Irrigation and water conservancy Projects [J]. *Henan water conservancy and south-north water diversion project*, **48** ,5 (2019)
4. Lu Yunxi. Management problems in the construction of small water Conservancy projects [J]. *Water Conservancy Technical Supervision*, 3 (2018)
5. Zheng Jiarong, GONG Huili, LI Qingyuan, et al. Analysis of settlement control factors in Beijing Plain area from 2003 to 2009 based on PS-INSAR. *Bulletin of Surveying and Mapping*, 12 (2014)
6. Li Jiashan, Li Xiaowei. On the settlement monitoring technology of foundation subsidence area: Take the first Avenue of Qunli and rainwater pumping Station of Harbin as an example [J].*Information on forestry science and technology*, **51**, 2 (2019)
7. Wang Lu, GUI Zhanfei. Application of GM-ARMA-BP Composite Model in building Settlement Prediction [J]. *Beijing surveying and mapping*, **33**, 9 (2019)
8. Feng Shaoquan, Hua Xianghong, Tao Wuyong, et al. A Prediction model of pier settlement for high-speed Railway Based on GA-BP-MC Neural Network [J].*Bulletin of Surveying and Mapping*, (2019)
9. Song Chuping. An Improved BP Neural Network Method for deep Foundation Pit deformation prediction [J]. *Journal of civil engineering and management*, **36**, 5 (2019)
10. Li Wanglin, Tang Fuyu. Application of BP Neural Network in settlement Modeling of Composite Foundation [J]. *Water Resources Planning and Design*, 2 (2007)