Prediction Model of Soil Electrical Conductivity Based on ELM Optimized by Bald Eagle Search Algorithm

Ying Huang, Hao Jiang, Weixing Wang and Daozong Sun

***Abstract*—Soil electrical conductivity is one of the indispensable and important parameters in fine agriculture management, and a suitable soil electrical conductivity can promote good plant growth. Prediction model of soil electrical conductivity is constructed to effectively obtain the conductivity values of soil, which can provide a reference basis for irrigation and fertilization management and prediction evaluation in fine agriculture. Prediction model of soil electrical conductivity based on extreme learning machine (ELM) optimized by bald eagle search (BES) algorithm is proposed in this paper. In the prediction model, the input weights and bias values of the ELM network were optimized using the BES algorithm, and the performance of the model was evaluated with parameters such as mean square error (MSE), coefficient of determination (R^2). Also, the correlations of parameters such as soil temperature, moisture content, pH, and water potential in the soil conductivity prediction model were determined using the exploratory data analysis (EDA) and HeatMap heat map tools. Finally, the proposed model was compared with back propagation neural network (BP), radial basis function networks (RBF), support vector machine (SVM), gated recurrent neural network (GRNN), long short-term memory (LSTM), particle swarm algorithm (PSO) optimization ELM, genetic algorithm (GA) optimized ELM prediction model. The experimental results showed that MSE, R^2 of the proposed model are 4.09 and 0.941, which are better than the other models. Also the results verified the effectiveness of the proposed method, which is a feasible prediction method to guide the irrigation and fertilization management in fine agriculture, because of its good prediction effect on soil conductivity.**

***Index Terms*—Soil electrical conductivity, prediction model, Machine learning, precision agriculture**

Original Research Paper
DOI: 10.53314/ELS2125050H

Manuscript received 25 March 2021. Received in revised form 18 June 2021. Accepted for publication 6 July 2021.

Ying Huang is a PhD student in the Electronic Information School, Wuhan University and with the Faculty of Liuzhou Railway Vocational Technical College, Liuzhou Guangxi, China (e-mail: hy@ltzy.edu.cn).

Hao Jiang is with Faculty of Electronic Information School, Wuhan University, Wuhan Hubei, China (corresponding author, e-mail: jh@whu.edu.cn).

Weixing Wang and Daozong Sun are with School of Electronic Engineering, South China Agricultural University, Guangzhou Guangdong, China (e-mail: Weixing@scau.edu.cn and sundaozong@scau.edu.cn).

I. Introduction

The material exchange between plants and nature is done through the root system. The root system is an important source of water and nutrients for plants, and its growth state reflects the growth and development of plants [1]. There are many factors influencing root development, among which soil moisture content and soil conductivity are two more important factors. Proper soil moisture content and electrical conductivity can promote good plant growth. Too low or too high soil moisture content can negatively affect the physiological activities of the root system [2]. The soil electrical conductivity directly reflects the salinity of the soil. High salinity in the soil will directly lead to the failure of the crop to grow and even lead to the death of the crop root system by dehydration. Soil electrical conductivity is an indispensable and important parameter for the study of precision agriculture, so it is important to construct a soil electrical conductivity prediction model to effectively obtain the electrical conductivity values of soil for formulating and guiding the management of agricultural irrigation and fertilization, and also to lay the foundation for the popularization of modern fine agriculture [3].

In recent years, the application of IoT technology and artificial intelligence technology in agriculture has become more and more common, and the research of prediction models of soil electrical conductivity in combination with sensor technology has become a hot spot. Cai et al. proposed a method of salt-effected soil information extraction based on a support vector machine with texture features, which can effectively extract information and classify saline soils [4]. Ghorbani et al. optimally developed a multilayer perceptron using a firefly algorithm to estimate EC values by combining some factors such as loam texture, cation exchange, and drainage [5]-[6]. Singh et al. implemented five data-driven techniques and their wavelet forms to predict soil permeability [7]. Gao et al. predicted soil moisture content and electrical conductivity in citrus orchards using IoT and LSTM [8]. Amirhosein Mosavi et al. constructed and evaluated a multilayer perceptron (MLP)-grey wolf hybrid machine learning model to analyze the correlation between electrical conductivity and parameters of soil organic matter. Sahana Mehebub et al. used a salinity index assessment model derived from measured soil electrical conductivity and remote sensing data [9]. Zhao Hui et al. used partial least squares regression (PLSR) and support vector machine (SVM) to construct an estimation model for hyperspectral data of soil electrical conductivity [10].

There is an upward trend in approaches to modeling relatively complex input features, such as artificial neural network models (ANN), ELM models, and RBF models, which have an advantage in their ability to examine linear and nonlinear interactions between input and output variables. Proper modeling in an attempt to find the hidden patterns of complex problems is essential for accurate prediction.

Although soil salinity is considered a well-recognized phenomenon in irrigated agriculture, only a few researchers have developed data-driven salinity models and investigated the relationship between them [11]. Moghadas et al. used a neural network-based forward solver for soil electrical conductivity imaging [12]. K.K. Benke, S et al. used machine learning to develop soil electrical conductivity and organic meandering functions for carbon content prediction [13]. The usefulness of such models is expected to play an important role in making fine agricultural management strategies.

The main objective of this study is to propose a prediction model of soil electrical conductivity. The model is based on joint use of extreme learning machine (ELM), which is an artificial neural network (ANN), and Bald Eagle search algorithm (BES), which is an iterative optimization algorithm with global search capability, which is expected to study the prediction of soil electrical conductivity based on parameters such as soil temperature and humidity, pH value, and soil moisture content. Finally, the prediction model is used for formulating and guiding the management of agricultural irrigation and fertilization. The first chapter introduces soil electrical conductivity and the current status of its research; the second chapter describes the method of data acquisition; the third chapter is the construction of the soil electrical conductivity prediction model; the fourth chapter is the model evaluation results and analysis; and finally, the conclusion and discussion.

II. Materials and Methods

A. Soil Information Collection System

The soil information acquisition system is constructed, which is composed of sensor circuits, single-chip module circuits, wireless communication modules, and solar panel power supply circuits. The sensor circuit mainly includes soil temperature, soil moisture content, soil electrical conductivity, pH value, and soil water potential sensor circuits, which are mainly responsible for real-time collection of tea garden soil information; the core of the single-chip module circuit is the STM32F103C8T6 single-chip microcomputer, which is mainly responsible for data processing; the wireless communication module is mainly composed of GPRS The module is mainly responsible for transmitting data to the remote server, which are shown in Fig. 1.

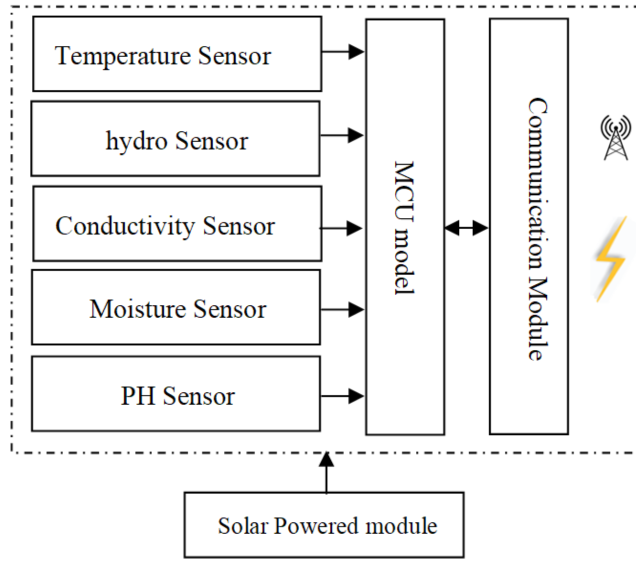

Fig. 1. System structure diagram

B. Data Processing

The data collection experiment was conducted on the campus of South China Agricultural University in Guangzhou, Guangdong Province. Data was collected from October 5, 2020, to November 16, 2020. Parameters such as soil moisture content, soil electrical conductivity, and soil temperature were calculated for each interval of 1 h, 6 h, 12 h, and 24 h using the aggregated data package for that day. Because each environmental parameter has a different order of magnitude, it needs to be normalized in the data preprocessing stage. After averaging the preprocessed data for each node, correlation analysis was performed for each environmental parameter with soil moisture and conductivity, respectively [8].

III. BES-ELM Models

A. Bald Eagle Search (BES) Algorithm

Bald eagle search (BES) algorithm is a new metaheuristic algorithm proposed by Malaysian scholar Alsattar in 2020, which has powerful global search capability and can effectively solve various complex numerical optimization problems. The main principle is to simulate the predatory behavior of the bald eagles and divide it into three phases: select stage, search stage, and swooping stage [14]-[15].

In the select stage, bald eagles randomly select the area to search food and then select the best area by judging the number of the preys. The position of the bald eagle is mainly determined by prior experience and position change parameters, as shown in:

$$P_{i,new} = P_{best} + \alpha \times \gamma \times (P_{mean} - P_i) \tag{1}$$

where α represents the position change control parameter that takes a value between 1.5 and 2, γ is a random number between 0-1, P_{best} represents when the bald eagle has the best search position identified during their previous search, P_{mean} indicates that these eagles have used up all information from the previous points, and P_i is the position of the i-th bald eagle.

In the search stage, the bald eagle flies in a spiral shape to search for prey within the selected search space, and moves in different directions within the spiral space to speed up its search, and then finds the best dive capture position. At this time, the best position of the bald eagle is determined by the equations (2)-(5).

$$P_{i,new} = P_i + x(i)\times\left(P_i - P_{mean}\right) + y(i)\times\left(P_i - P_{i+1}\right) \tag{2}$$

$$x(i) = \frac{\mathrm{xr}(i)}{\max(|xr|)} \qquad y(i) = \frac{\mathrm{yr}(i)}{\max(|yr|)} \tag{3}$$

$$xr(i) = r(i)\times\sin(\theta(i)) \qquad yr(i) = r(i)\times\cos(\theta(i)) \tag{4}$$

$$r(i) = \theta(i) + R\times rand \qquad \theta(i) = \varphi\times\pi\times rand \tag{5}$$

where $\theta(i)$ and $r(i)$ represent the polar angle and polar diameter of the spiral equation, φ is a parameter determining the corner between point search in the central point that takes a value between 5 and 10, and R is an parameter determining the number of search cycles that takes a value between 0.5 and 2, *rand* is a random number from 0-1, $x(i)$ and $y(i)$ indicate the position of the bald eagle in polar coordinates.

In the swooping stage, the bald eagle quickly flies to the target prey from the best position in the search space, and other individuals in the population also move to the best position and attack the prey at the same time. At this time, the position of the vulture is calculated.

$$\begin{aligned} P_{i,new} &= \mathrm{rand}\times P_{best} + x1(i)\times\left(P_i - c1\times P_{mean}\right) + \\ &+ y1(i)\times\left(P_i - c2\times P_{best}\right) \end{aligned} \tag{6}$$

$$x1(i) = \frac{\mathrm{xr}(i)}{\max(|xr|)} \qquad y1(i) = \frac{\mathrm{yr}(i)}{\max(|yr|)} \tag{7}$$

$$xr(i) = r(i)\times\sin\mathrm{h}(\theta(i)) \quad yr(i) = r(i)\times\cos\mathrm{h}(\theta(i)) \tag{8}$$

$$\theta(\mathrm{i}) = \mathrm{a}\times\pi\times rand \qquad \mathrm{r}(i) = \theta(i) \tag{9}$$

where c1 and c2 are parameters that can increase the movement intensity of bald eagles toward the best and center points that take the value between 1 and 2.

B. Extreme Learning Machine (ELM)

ELM is a new fast learning algorithm proposed by Huang Guangbin to improve the BP algorithm to improve the learning efficiency and simplify the setting of learning parameters, which has the advantages of fast learning rate and good generalization performance [16]-[17].

Suppose that there are N samples (x_i, t_i), and that are shown in:

$$X_i = \left[x_{i1}, x_{i2}, \cdots, x_{in}\right]^T \in R^n \tag{10}$$

$$t_i = \left[t_{i1}, t_{i2}, \cdots, t_{in}\right]^T \in R^m \tag{11}$$

Therefore, a single hidden layer neural network with L invisible nodes can be expressed as:

$$\sum_{i=1}^{L}\beta_i g\left(W_i\cdot X_j + b_i\right) = o_j \qquad j = 1,2,\cdots,N \tag{12}$$

where $g(x)$ represents the activation function, $W_i = [w_{i1}, w_{i2}, \ldots, w_{in}]^T$ indicates input weights, β_i indicates output weights, b_i is The bias of the i-th hidden layer unit.

The ELM network structure is shown in the Fig. 2.

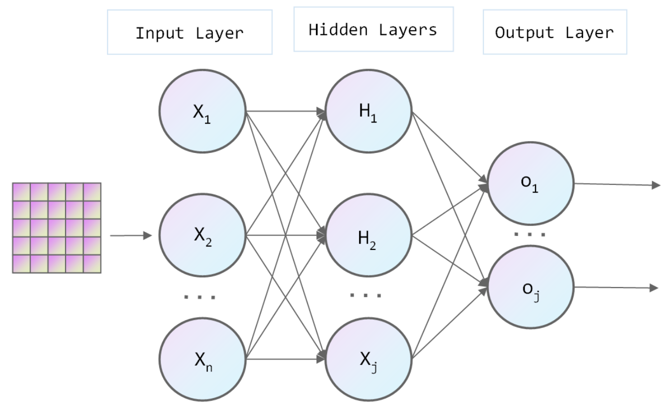

Fig. 2. ELM network structure diagram

The goal of learning is to minimize the output error, which expressed as:

$$\sum_{\mathrm{j}=1}^{N}\left\|o_j - t_j\right\| = 0 \tag{13}$$

In other words, there are three parameters (β_i, b_i and W_i) that make the following formula (14) true.

$$\sum_{i=1}^{L}\beta_i g\left(W_i\cdot X_j + b_i\right) = \mathrm{t}_j \qquad j = 1,2,\cdots,N \tag{14}$$

It can be expressed in a matrix, as shown in:

$$H\beta = T \tag{15}$$

where H is the output of the hidden layer node, β is the output weight, and T represents the output expected.

We can find the optimal value $\hat{\beta}_i$, $\hat{b}_i$ and $\hat{W}_i$ to ensure the goal, which is given in:

$$\left\|\mathrm{H}\left(\hat{\mathrm{W}}_i, \hat{b}_i\right)\hat{\beta}_i - T\right\| = \min_{W,b,\beta}\left\|\mathrm{H}\left(\mathrm{W}_i, b_i\right)\beta_i - T\right\| \qquad \mathrm{i} = 1,2,\cdots,L \tag{16}$$

C. BES-ELM Modula

The initial input weights and bias settings of ELM have an important impact on the recognition results of the network. The ELM's input weights and biases are optimized by BES to ensure the minimum value of its fitness objective function, which is shown in:

$$E=\sum_{j=1}^{N}\left(\sum_{i=1}^{L}\beta_{\mathrm{i}}g\left(W_i\cdot X_j+b_i\right)-t_j\right)^2 \tag{17}$$

First, the ELM model is used to predict the output of the input parameters, find the error with the expected value, and use it as the fitness value of the BES algorithm. BES finds the optimal fitness value based on this fitness value and determines the optimal position of the bald eagle, and then inputs it as the optimal input weight and bias to the ELM for training, and continues the cycle until the condition is satisfied.

IV. Experiments and analysis

A. Evaluation Indicators

To validate the performance of the algorithm, the evaluation metrics are measured using the mean square error (*MSE*) and the coefficient of determination (R^2) [18], and the error (Error) of the entire test sample is also an indicator, which is defined in:

$$MSE=\frac{1}{M}\sum_{n=1}^{M}\left(y_p-y_r\right)^2 \tag{18}$$

and

$$R^2=\frac{\sum_{n=1}^{M}\left(y_p-\overline{y_r}\right)^2}{\sum_{n=1}^{M}\left(y_{\mathrm{r}}-\overline{y_r}\right)^2} \tag{19}$$

where y_p represents the predicted value, y_r represents the measured value, $\overline{y_p}$ represents the mean of the measured value, and M represents the sample value.

And error is calculated by the norm function.

B. Data Correlation Experiment

Data were collected from October 5 to November 16, 2020, and the average values of soil moisture content, soil water potential, soil electrical conductivity, soil temperature, and pH value were calculated for each 1-hour interval, for a total of 635 sets of data. EDA (Exploratory Data Analysis [18] and HeatMap heat map tools were used to analyze the correlation between individual soil moisture content, soil electrical conductivity, soil water potential, soil temperature, and pH value, as shown in Fig. 3.

In Fig.3, the abbreviated form is used for display convenience. Conductivity represents soil electrical conductivity, Moisture represents soil moisture content, pH represents pH value, Hydro represents soil water potential, and Temperature represents soil temperature.

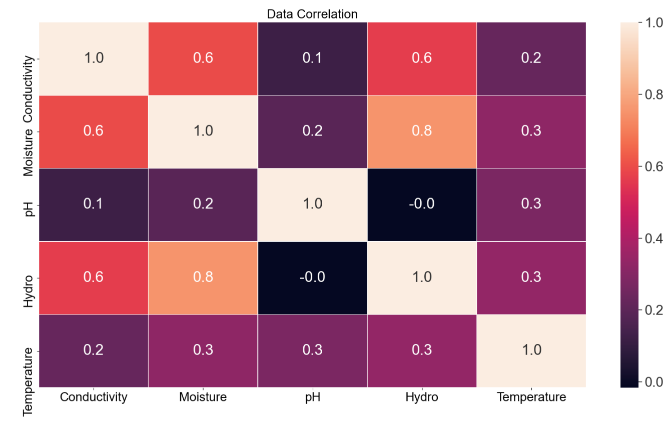

Fig. 3. Data correlation analysis

The numbers in the graph represent the correlation coefficient matrix. The larger the value, the greater the correlation is. It shows moderate to high correlation between the soil electrical conductivity on one hand and the soil moisture content and soil water potential on the other, both around 0.6, which indicates that soil electrical conductivity is more influenced by moisture content and soil water potential, and the correlation of soil electrical conductivity with soil temperature and pH was only 0.2 and 0.1, which indicates that soil conductivity is less influenced by soil temperature and pH value.

From the figure, it is found that soil electrical conductivity is most correlated with soil moisture content and soil water potential, as such is soil temperature and pH value.

C. Application of BES-ELM Modula

The choice of input parameters in the prediction model plays an important role in the accuracy of the prediction results. The parameters collected in this system are mainly soil water content, soil water potential, soil temperature, pH value, and soil electrical conductivity, where the soil electrical conductivity is collected mainly to verify the accuracy of the model prediction. Data correlation experiment mentioned above shows moderate to high correlation between the soil electrical conductivity on one hand and the soil moisture content and soil water potential on the other, both around 0.6, which means that soil water content and soil water potential have a relatively large effect on soil conductivity. Therefore, soil moisture content and soil water potential can be used as inputs to the prediction model. Although soil temperature and pH have a slightly smaller effect on soil electrical conductivity, they can also be used as inputs to the prediction model if necessary to increase the accuracy of the model predictions.

The steps of the algorithm are described as follows.

Step 1: Data processing. The data were preprocessed using the [0, 1] standardization, and the abnormal values were eliminated by 3σcriterion. 500 sample data were randomly selected as the training set, and the remaining 135 sample data were used as the test set to train and test the soil conductivity prediction model.

Step 2: Initializing the parameters of the BES algorithm and ELM network, which is presented in Table I.

Step 3: Initialize the input weights, output weights, and bias

Step 4: Set the fitness function. The mean square error (MSE) is chosen as the fitness function of the optimization-seeking algorithm. Given the input training and test datasets, the fitness values can be calculated based on the ELM network. Then, given the value of the fitness function, the condor uses the formula (1)-(9) mentioned above to continuously update the position until the best solution obtained in the population for solving the problem.

Step 5: The ELM's input weights, biases, and output weights are optimized by BES to ensure the minimum of the ELM's fitness objective function.

Step 6: Substitute the optimized parameter values into ELM neural network for prediction and output the results.

D. System Model Analysis

The data were collected from October 5 to November 16, 2020, and the average values of soil moisture content, soil water potential, soil conductivity, soil temperature, and soil moisture were calculated for every 1-hour interval, with a total of 635 sets of data. 500 sets of these data were selected as the training set and the remaining 135 sets were used as the test set. The specific parameters of the experiment are shown in Table I.

TABLE I
EXPERIMENT PARAMETERS

Module	Variables	Value
BES	α	1.5
	a	10
	R	1.5
	C1	2
	C2	2
	N	100
	Maxiter	100
ELM	Input	4
	hidden	100
	output	1

The average values of soil moisture content, soil water potential, soil temperature, and soil PH at 1-hour intervals were used as the input values of the model, and soil electrical conductivity was used as the output value, and the experiments were conducted according to the values of the network parameters set above. The results of ELM prediction, BES-ELM prediction, and error values are shown in Figs. 4-6.

From the figure, it is found that the *MSE*, R^2, and overall error values predicted by ELM are 45.5511, 0.39886, and 78.4181, respectively, while the *MSE*, R^2, and overall error values of BES-ELM are 4.482, 0.93592, and 24.5983, respectively. This is because ELM is randomly generated input weights and bias values, and the prediction is less effective, while BES-ELM is optimized using the bald eagle search algorithm to ensure that the error between the output value and the expected value is controlled to the minimum value, and the performance of BES-ELM is far better than the ELM effect. The figure shows that BES-ELM has the smallest error rate, short prediction time,

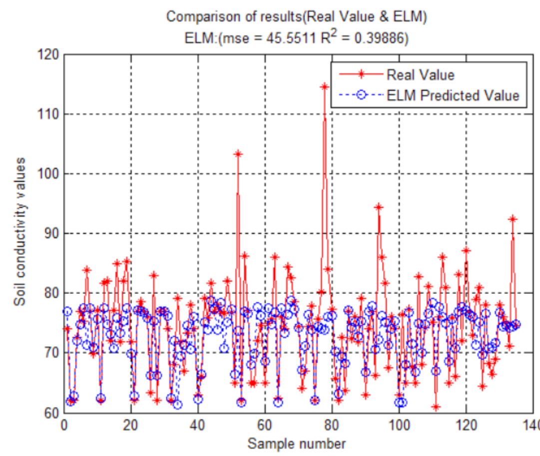

Fig. 4. Comparison of real values and predicted values using ELM

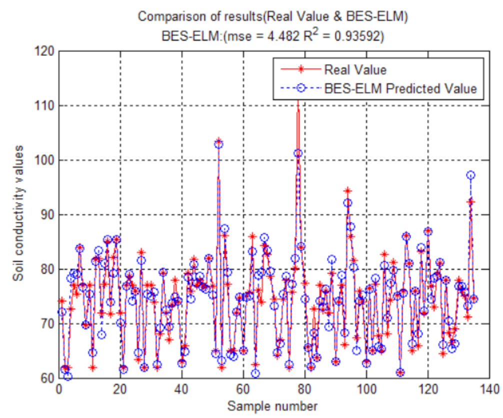

Fig. 5. Comparison of real values and predicted values using BES-ELM

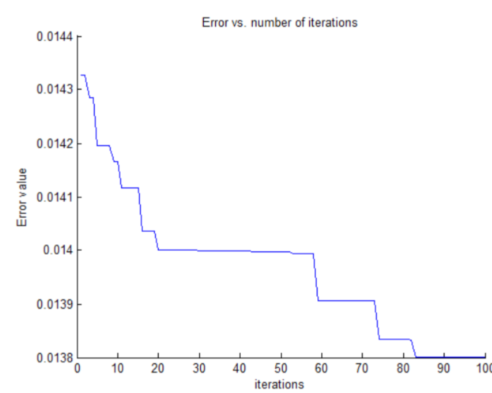

Fig. 6. Variation of error and number of iterations

good fit to the actual value curve, prediction results closer to the actual value, minimal oscillation in the overall relative error curve, and a smoother relative error curve. This indicates that BES-ELM is a feasible method for predicting soil electrical conductivity with good prediction results.

E. Comparation with Existing Algorithms

To prove the validity of this prediction model, we will compare the performance of the algorithm with the existing algorithms. Algorithms used for comparison are back propagation neural network (BP) [19], radial basis function networks (RBF)

[20], support vector machine (SVM) [21], GRNN [22], LSTM [23], and two optimization ELM networks are constructed using particle swarm algorithm (PSO) [24], and genetic algorithm (GA) [24], and the corresponding networks are named PSO-ELM, and GA-ELM, respectively.

The prediction model proposed in this paper has relative advantages related to other models. The parameter values in the table are averaged over the results of 5 replicate experiments, which are shown in Table II.

Table II
ALGORITHM PERFORMANCE COMPARISON

Model	MSE	R^2
BP	26.08	0.614
RBF	17.94	0.802
SVM	30.84	0.674
GRNN	42.30	0.415
LSTM	45.80	0.826
PSO-ELM	27.30	0.665
GA-ELM	24.30	0.706
BES-ELM	4.09	0.941

Table II shows that the GRNN model has the worst prediction performance among the eight models, with *MSE* and R^2 of 42.30 and 0.415, respectively; the BP model and SVM model have slightly better prediction performance, with *MSE* and R^2 of 26.08 and 0.614 for the BP model, *MSE* and R^2 of 30.84 and 0.674 for the SVM model, and *MSE* and R^2 of 17.94 and 0.802 for the RBF model and LSTM model, respectively. The *MSE* and R^2 of the BP model are 26.08 and 0.614, the *MSE* and R^2 of the SVM model are 30.84 and 0.674, respectively, and the performance of the RBF and LSTM models are better, the *MSE* and R^2 of the RBF model are 17.94 and 0.802, respectively, and the *MSE* and R^2 of the LSTM model are 45.8 and 0.826, respectively. The BES-ELM model proposed in this paper has the best prediction performance among the eight models, with *MSE* and R^2 of 4.09 and 0.941, respectively. The algorithm proposed in this paper exhibits better model performance and prediction results.

In addition, there is no clear correlation between the *MSE* and R^2 of the model, i.e., a smaller *MSE* does not imply a higher R^2. Therefore, the *MSE* is not an optimal solution to measure model performance, illustrating that the performance of the model cannot be proven based on the *MSE* alone.

V. Conclusion

In this paper, a prediction model of soil electrical conductivity based on ELM optimized by the bald eagle search algorithm is proposed. Using a soil information collection system with a wireless sensor network, we can collect soil temperature, moisture content, conductivity, PH value, and water potential data in real-time and transmit the data to a remote server using wireless sensor network technology, to construct a soil electrical conductivity prediction model and use the ELM and BES-ELM models were used for prediction. Our work is summarized as follows.

- Soil electrical conductivity data acquisition. Parameters such as soil temperature, moisture content, conductivity, pH, and water potential were collected in real-time using a sensor circuit, and the data were transmitted to a remote server via a wireless sensing network. A real-time soil information collection system for tea plantations was constructed.
- The correlation of the parameters in the soil electrical conductivity prediction model was determined. The correlation of each parameter was analyzed by using EDA and HeatMap heat map, and the correlation of soil electrical conductivity was determined, with the highest correlation with soil moisture content and soil water potential, followed by soil temperature and PH value.
- A soil electrical conductivity prediction model based on the bald eagle search algorithm to optimize ELM was constructed. The principles of ELM and BES algorithm are described, and the input weights and bias values of the ELM network are optimized using the BES algorithm, which effectively improves the performance of the network. And the optimized BES-ELM network cloud was used to construct a soil electrical conductivity prediction model. Soil water potential, and soil moisture content were used as input values and soil electrical conductivity was used as output value to achieve soil electrical conductivity prediction. Soil temperature and pH have a slightly smaller effect on soil electrical conductivity; they can also be used as inputs to the prediction model to increase the accuracy of the model prediction.
- Comparation with existing algorithms is also the research task of this paper. Monitoring data from tea plantations in Liucheng County were used as the original experimental sample data to train and predict the BES-ELM soil conductivity prediction model, and the performance was compared with BP, RBF, GRNN, SVM, LSTM, PSO-ELM and GA-ELM prediction models. The experimental results show that the BES-ELM model has relative advantages related to other models. Using the method proposed in this paper can provide certain guidance for irrigation and fertilization in tea plantations, and can also predict the soil conductivity in the future period based on the BES-ELM prediction model, combining the meteorological data and current soil information of tea plantations in the future period, to grasp its change trend in time and facilitate tea garden managers to prepare for fertilization and irrigation in advance, which can help realize scientific and fine irrigation and fertilization management of tea plantations and bring better management benefits.

Some issues in the paper also need to be further discussed. Refinement of the soil electrical conductivity model is needed. Since soil electrical conductivity is more influenced by other factors in the environment, further in-depth research is needed to study the relationship between soil moisture content rated to get better results.

Acknowledgment

This research was funded by 2018 Guangxi University High-level Innovation Team and Excellence Scholars Program (Guijaioren [2018]No.35); 2021 Guangdong Province Modern Agricultural Key Technology Model Integration and Demonstration and Promotion Project, Guangdong Province Science and Technology Special Funds ("Big Special + Task List") Project (2020020103); Guangdong Province Education Department Special Innovation Class Project (2019KTSCX013); Key-Area Research and Development Program of Guangdong Province (2019B020214003).

References

[1] SUN, D. Z., WANG, W. X., HUANG, Y, et al. "Monitoring and analysis of tea root parameters based on CI600 in situ root imager." *Applied Ecology and Environmental Research,* vol. 17, no.6, pp.15301-15309, (2019)

[2] LAI Chengchun, HUANG Xiangui, WANG Qi, et al. "Effect of fruit growth and soil moisture content on fruit cracking for Murcott tangerine." *Journal of Fujian Agriculture and Forestry University (Natural Science Edition)*, vol.48, no. 4, pp. 434-439, (2019).

[3] Agricultural Chemistry Committee of Chinese Soil Society, ed. *Routine analytical methods of soil agro chemistry*. Beijing: Science Press, 1983.

[4] Cai, S.M., Zhang, R.Q., Liu, L.M., et al. "A method of salt-effected soil information extraction based on a support vector machine with texture features." *Math. Comput. Model.,*vol. 51, no. 11-12, pp. 1319–1325,(2010).

[5] Ghorbani, M.A., Shamshirband, S., Zare Haghi, D., et al. "Application of firefly algorithm-based support vector machines for prediction of field capacity and permanent wilting point." *Soil Tillage Res.* No. 172, pp. 32–38, (2017).

[6] Ghorbani, M.A., Deo, R.C., Kashani, et al. "Artificial intelligence-based fast and efficient hybrid approach for spatial modelling of soil electrical conductivity," *Soil Tillage Res*, no.186, pp.152–164, (2019).

[7] Singh, V.K., Kumar, D., Kashyap, P.S., et al. "Modelling of soil permeability using different data driven algorithms based on physical properties of soil," *J. Hydrol,* 580. DOI: 10.1016/j.jhydrol.2019.124223

[8] GAO Peng, XIE Jiaxing, SUN Daozong, et al. "Prediction models of soil moisture content and electrical conductivity in citrus orchard based on internet of things and LSTM." *Journal of South China Agricultural University,* vol.41, no.6, pp.134-144, (2020).

[9] Sahana Mehebub, Rehman Sufia, Patel Priyank Pravin, et al. "Assessing the degree of soil salinity in the Indian Sundarban Biosphere Reserve using measured soil electrical conductivity and remote sensing data–derived salinity indices." *Arabian Journal of Geosciences,* vol.13,no.24,(2021). DOI: 10.1007/s12517-020-06310-w

[10] ZHAO Hui, LI Xinguo, NIU Fangpeng, et al. "Hyperspectral estimation model of the soil conductivity in the lakeside oasis of Bosten Lake, China." *Soil and Fertilizer Sciences in China.* [Online].1-9, 2021,. Available: http://iras.lib.whu.edu.cn:8080/rwt/401/http/NNYHGLUDN3WXTLUPMW4A/kcms/detail/11.5498.S.20201109.1339.002.html.

[11] Mosavi Amirhosein, Samadianfard Saeed, Darbandi Sabereh, et al. "Predicting soil electrical conductivity using multi-layer perceptron integrated with grey wolf optimizer." *Journal of Geochemical Exploration,* 220, (2021).DOI: 10.1016/j.gexplo.2020.106639

[12] Moghadas D, Behroozmand A A, Christiansen A V. "Soil electrical conductivity imaging using a neural network-based forward solver: Applied to large-scale Bayesian electromagnetic inversion." *Journal of Applied Geophysics,* 104012, (2020). DOI:10.1016/j.jappgeo.2020.104012

[13] K.K. Benke, S. Norng, N.J. Robinson, et al. "Development of pedotransfer functions by machine learning for prediction of soil electrical conductivity and organic carbon content." *Geoderma,* 366, (2020).DOI: 10.1016/j.geoderma.2020.114210

[14] Alsattar H A, Zaidan A A, Zaidan B B. "Novel meta-heuristic bald eagle search optimisation algorithm." *Artificial Intelligence Review: An International Science and Engineering Journal,* vol.53, no.8, pp.2237-2264,(2020).DOI: *10.1007/s10462-019-09732-5*

[15] Jia Heming, Jiang Zichao, Li Yao. "Simultaneous optimal feature selection based on improved condor search algorithm." *Control and Decision.* [Online].1-9, 2021. Available: https://doi.org/10.13195/j.kzyjc.2020.1025.

[16] Guang-Bin Huang, Qin-Yu Zhu, Chee-Kheong Siew. "Extreme learning machine: a new learning scheme of feedforward neural networks." *IEEE International Joint Conference on Neural Networks, Budapest, Hungary,* no.2, pp.985-990, (2004).

[17] Huang, G., Huang, G. B., Song, S., et al. "Trends in extreme learning machines: A review." *Neural Networks,* no.61, pp.32-48, (2015). DOI: 10.1016/j.neunet.2014.10.001

[18] NASH J E, SUTCLIFFE J V. "River flow forecasting through conceptual models-part I: A discussion of principles." *J Hydrol,* vol.10, no.3, pp.282-290, (1970).

[19] Rumelhart D E, Hinton G E, Williams R J. "Learning Internal Representation by Back-Propagation Errors." *Nature,* no.323, pp.533-536, (1986). DOI: 0.1029/93JA01471

[20] Sosa J, Buitrago L. "Time-varying coefficient model estimation through radial basis functions." *Journal of Applied Statistics,* pp.1-25,(2021). DOI: 10.1080/02664763.2021.1910938.

[21] Wang X, Li Z, Zhang Y. "Model for Predicting the Operating Temperature of Stratospheric Airship Solar Cells with a Support Vector Machine." *Energies,* vol.14, no.5, pp.1228, (2021).

[22] Specht D F. "A general regression neural network." *IEEE Transactions on Neural Networks,* vol.2, no.6, pp.568-576, (1991). DOI: *10.1109/72.97934*

[23] MAJHI B, NAIDU D, MISHRA A P, et al. "Improved prediction of daily pan evaporation using Deep-LSTM model." *Neural Comput Appl,* vol.32, no.12, pp. 7823-7838, (2020). DOI: 10.1007/s00521-019-04127-7

[24] Jahandideh-Tehrani M, Jenkins G, Helfer F. "A comparison of particle swarm optimization and genetic algorithm for daily rainfall-runoff modelling: a case study for Southeast Queensland, Australia." *Optimization and Engineering,* vol.22,no.1,(2021). DOI: 0.1007/s11081-020-09538-3