Nonlinear Correction of LVDT Sensor Based on ACO-BP Neural Network

Li Minghui, Gong Qiangling*, Wu Wenkai, Hai Hongyu, Ma Chenpei, Che Chang

College of Mechanical & Electrical Engineering, Shaanxi University of Science & Technology, Xi’an Shaanxi 710021, China

* Corresponding author’s e-mail: 1805020@sust.edu.cn, 1624820300@qq.com

Abstract. In this paper, the output signal of the linear variable differential transformer type displacement sensor (LVDT) is nonlinear, a BP neural network optimized by the ant colony algorithm is designed to fit and correct the nonlinear output of the LVDT. This scheme first uses the ant colony algorithm to search the optimal range of neural network weights and thresholds, and then uses the BP neural network to fit any non-linear function to LVDT nonlinear output fitting and correction, which overcomes the shortcomings of BP neural network easily falling into local minimum and slow convergence. Through MATLAB simulation experiments, it is concluded that the convergence speed, average error and average error percentage of the ACO-BP neural network are better than the BP neural network. This solution has certain feasibility for solving the LVDT nonlinear problem, and provides a new solution for the sensor nonlinear correction.

1. LVDT displacement sensor analysis

Linear variable differential transformer (LVDT) displacement sensor is a sensor that converts linear displacement into analog voltage. It can perform non-contact displacement measurement. It has the advantages of simple structure, fast response speed, high resolution and long service life. It is widely used in all walks of life in the national economy [1].

LVDT displacement sensors are divided into two-stage, three-stage, four-stage and five-stage according to the arrangement of primary and secondary coils and their quantitative relationship. The mechanical structure of LVDT discussed in this article adopts a three-stage structure [2].

The three-segment LVDT is composed of a primary coil, two secondary coils, a freely moving iron core, a coil frame and a casing (as shown in Figure 1). Among them: N1 is the primary coil, N21 and N22 are the two secondary coils, and L is the movable iron core.

The middle of the LVDT shell is the primary coil, and a secondary coil is symmetrically distributed on the left and right sides. A freely movable rod-shaped core runs linearly in the coil group to provide a path for the magnetic flux of the coil. The two secondary coils are wired in reverse series, and the difference between the output voltages of the two secondary coils is the output voltage of the LVDT sensor.
When the primary coil is energized, according to Faraday's law of electromagnetic induction, when the iron core cuts the magnetic induction line in the magnetic field, the two secondary coils will generate a voltage, and the mutual inductance between the LVDT primary coil and the two secondary coils will change with the core displacement [3]. In an ideal situation, the output voltage value of the LVDT sensor is linearly related to the displacement of the iron core.

In fact, the input and output of most sensors are non-linear, and the measurement system cannot obtain the measured information truly and accurately. This error will greatly reduce the accuracy of the LVDT sensor measurement. Therefore, it is particularly important to perform nonlinear correction on LVDT sensors.

BP neural network has strong nonlinear fitting ability. However, which has shortcomings such as slow convergence speed and low accuracy. The literature [4] compares ACO-BP neural network with GA-BP neural network, which reflects the former's generalization ability and successful training advantages in terms of rate and algorithm stability. In this paper, the ant colony algorithm has a good global search ability, which is used to optimize the BP neural network, and the optimized ACO-BP neural network is used to perform LVDT nonlinear correction, finally the MATLAB simulation experiment.

2. BP neural network model

2.1. BP neural network

BP neural network, also known as multi-layer feed-forward neural network, it is a topological structure of three-layer feed-forward neural network. Its structure is composed of input layer, hidden layer and output layer [5]. As shown in Figure 2, each layer is composed of many simple neurons in parallel operation. The state value of these neurons will affect the relationship between the input layer and the output layer.

Figure 2. BP neural network structure diagram
The basic idea of BP neural network is the gradient descent method, which uses the gradient search technique to minimize the mean square error of the actual output value and expected output value of the network [6]. The characteristics of this neural network model are: simple structure, stable working state, and easy hardware implementation.

2.2. BP neural network algorithm process
The basic idea of the BP neural network algorithm is to divide the training process into two stages: the first stage is the forward propagation process, the input information from the input layer undergoes the operation of weights and thresholds to the hidden layer, and the hidden layer undergoes the operation of weights and thresholds Reach the output layer. If the operation results in the output layer cannot meet the end requirements of the algorithm, then go to the next stage; the second stage is the back propagation process, the error calculation results from the output layer to the hidden layer, from the hidden layer to the input layer, During the return process, the weight of each layer of neuron connection is modified one by one by gradient descent method [7]. The BP neural network iteration the process continuously. If the signal error is within the allowable range, the algorithm ends.

3. Research on ant colony algorithm to optimize BP neural network

3.1. The basic idea of optimization algorithm
In the neural network algorithm, the selection of weights and thresholds is random. The weights and thresholds are continuously updated as the number of algorithm evolutions increases. This random selection process usually leads to an increase in the number of iterations of the algorithm, an increase in running time, and a decrease in optimization accuracy, which affects the execution efficiency of the algorithm. The training process of BP neural network is equivalent to the process of solving the optimal solution, that is, to find a set of optimal weight and threshold combination [8]. In order to overcome the problem of random selection of weights and thresholds, a BP neural network training method optimized by ant colony algorithm is proposed, namely ACO-BP neural network algorithm. Using the global optimization ability of the ant colony algorithm, the initial selection and threshold of the BP neural network are optimized, and then the optimized weight threshold is brought into the corresponding algorithm, which can improve the BP network's vulnerability to local minima and convergence speed. Defects such as slowness and oscillating effects can produce prediction results with the smallest error.

3.2. ACO-BP optimization process
The specific optimization process of ACO-BP neural network algorithm is as follows:

(1) Initialize relevant parameters. Suppose the pheromone of the element $j$ in the set $I_p(1 \leq i \leq m)$ is $T_j(I_p(t)) = C$, $(1 \leq j \leq N)$, the number of ants is $M$, and all ants are in the nest at the beginning $In$, the maximum number of iterations is $N_{max}$.

(2) Ants find their way. All ants $k = \{1,2,3, ..., M\}$ start from the set $I_p$ to find the food source, and select the $j$ element according to the following probability:

\[
\text{Prob}(t_j^k(I_p)) = \frac{(t_j(I_p(t)))}{\sum_{u=1}^{N} t_u(I_p)}
\]  

(1)

(3) Generate the best route and update the pheromone. After all ants select an element in each set, the weights selected by all ants are used as the parameters of the neural network to calculate the output error of the training sample and the optimal value of the selected parameter this time. Let the time taken for this process be $m$, so the formula for updating the set $I_p(1 \leq i \leq m)$ global pheromone is:

\[
T_j(I_p(t+1)) = \rho T_j(I_p(t)) + \Delta T_j(I_p)
\]  

(2)

In the formula: $\rho$ ($0 \leq \rho \leq 1$) represents the persistence of the pheromone, that is, the remaining pheromone, then $1-\rho$ represents the volatile part of the pheromone from $t$ to $t+m$.

\[
\Delta T_j(I_p) = \sum_{k=1}^{N} \Delta t_j^k(I_p)
\]  

(3)

In the formula: $\Delta t_j^k(I_p)$ means the remaining pheromone of the $j$–th element in the set $I_p$ of the $k$th ant in the cycle $P_j(I_p)$, the calculation formula is as follows:
\[
\Delta t^k(I_{pi}) = \begin{cases} 
\frac{Q}{e^k} & k \in I_{pi} \\
0 & \text{else}
\end{cases}
\] (4)

In the formula: the parameter Q is a constant, which means the sum of all pheromones produced by the ants after completing a cycle, which mainly changes the adjustment rate of the pheromone; e is the element selected by the kth ant as the weight of the neural network. The maximum output error of all training samples is calculated as follows:

\[
e^k = \max\{|O_n - O_q| \quad n = \{1, 2, 3, ..., h\}
\] (5)

In the formula: h is the number of samples, \(O_n\) and \(O_q\) are the actual output and expected output value of the neural network. Therefore, the smaller the error, the more the pheromone increases.

(4) Sort by the mean square error of the actual output value and expected value of the BP network, and evaluate the best and worst ants

(5) Repeat steps (2) and (3) above. When all ants converge to the same path, the number of iterations is completed and the optimal solution is obtained.

(6) Learn the obtained optimal solution as the weight and threshold of the BP neural network, and repeat the above steps until the iteration termination condition is satisfied. Exit the program and the algorithm ends.

The process of ACO-BP neural network algorithm is shown in Figure 3.

![ACO-BP neural network algorithm flowchart](image)

**Figure 3. ACO-BP neural network algorithm flowchart**

**4. Experimental simulation and analysis**

**4.1. Simulation configuration**

MATLAB is a commercial mathematics software produced by MathWorks in the United States. It is used in advanced technical computing languages and interactive environments for algorithm
development, data visualization, data analysis, and numerical calculation, mainly including MATLAB and Simulink [9]. Through the software for modeling and simulation, it is convenient and quick to construct a suitable neural network.

The ant colony algorithm simulation parameters are shown in Table 1.

| Name                        | Parameter |
|-----------------------------|-----------|
| Total number of ants (M)    | 200       |
| Maximum number of iterations (NC) | 300       |
| Pheromone Volatility (Rou)  | 0.57      |
| Total pheromone (Q)         | 1.0       |
| Pheromone importance factor (alpha) | 1         |
| Heuristic function importance factor (beta) | 5         |

### 4.2. MATLAB simulation experiment

The input value and output value of the data to be simulated are in a one-to-one format, so in the BP neural network structure, both the input layer and the output layer are set with 1 node, and the hidden layer is set with 20 nodes. Therefore, the structure of BP neural network is 1-20-1, as shown in Figure 4.

![BP neural network structure diagram](image)

Use BP neural network and ACO-BP neural network for training respectively, set the maximum number of trainings to 2000, and the training results are shown in Figure 5.

![Minimum error 10^-4 training diagram](image)

It can be seen from Figure 5 that when the Mean Squared Error (MSE) is set to 10^-4, the BP neural network has not reached the set 10^-4 error after 2000 iterations of training, and the ACO optimization can reach an error of 10^-4. It can be seen that the training speed of the BP neural network is slow and the training accuracy is not high. The ACO-BP neural network is superior to the BP neural network in training speed.
Under the same training conditions, the average error of the BP neural network is 0.141 and the average error percentage is 1.01%; while the average error of the ACO-BP neural network is 0.045 and the average error percentage is 0.36%. It shows that the training accuracy of ACO-BP neural network is also better than that of BP neural network.

5. Conclusion
Aiming at the problem of non-linearity in the output part of the LVDT displacement sensor, a BP neural network optimized based on ant colony algorithm for non-linear fitting correction is proposed. Firstly, the initial weights and thresholds of the BP neural network are optimized through the ant colony algorithm, and then combined with the BP neural network has the characteristics of fitting any non-linear function, and the LVDT nonlinear output is corrected. The MATLAB simulation experiment proves that the ACO-BP neural network can realize the nonlinear correction of the LVDT sensor, and the correction accuracy and convergence speed are better than the BP neural network, and the system reliability is high. This solution has certain feasibility for solving the LVDT nonlinear problem, and provides a new solution for the sensor nonlinear correction.

References
[1] Ruan Jian, Zhu Zhaoliang, Li Sheng, et al. Research on calibration technique of LVDT[J]. Journal of Zhejiang University of Technology, 2016, 8, 44(2): 184-188.
[2] Liu Zhicai. Digital Signal Processing Algorithm and Circuit Research on LVDT Displacement Sensor [D]. Zhejiang University, 2012, 12-13.
[3] Yu Na, Bi Dongyun, Chai Shouchen, et al. Design of high-precision inductive displacement sensor based on LVDT [J]. Journal of Magnetic Materials and Devices, 2017, 048(003):40-42,54.
[4] Yin Shuyan, Du Qingdong. Research on Performance of ACO-BP Neural Network Based on Ant Colony Algorithm [J]. Scientific and Technological Innovation, 2015(22).
[5] Meng Yongyi. Fault Diagnosis of Regulating Valve Based on NMF Feature Extraction[J]. Journal of State Grid Technology College,2019,22(06):41-45.
[6] Jiang Biao, Li Rongzheng, Cao Lei. Design of LVDT Nonlinear Compensation Method Based on Neural Network Algorithm[J]. Control and Instruments In Chemical Industry,2017,44(09):853-856+908.
[7] Mo Rong, Tian Guoliang, Sun Huibin. Application of BP Neural Network with Genetic Algorithm to Roughness Prediction[J]. Mechanical Science and Technolo-ogy,2015,34(05):729-732.
[8] Xue Ping, Song Yanliang. The Prediction of Lead-Acid Battery Remaining Capacity Based on Improved Ant Colony Algorithm and BP Network[J]. Journal of Harbin University of Science and Technology, 2016, 021(006):95-99.
[9] Diao Shaowen. Design of The LVDT Displacement Measurement Sensor Circuit and Study on Nonlinear Correction[D]. Qingdao University of Technology,2018.