Optimization of Antenna Design Using the Artificial Neural Network and the Simulated Annealing Algorithm

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***Abstract*—A novel model for optimizing antenna design is proposed in this paper, combining the artificial neural network (ANN) with the simulated annealing (SA). The data set to train the ANN is obtained from the full-wave simulation software. The trained ANN can quickly predict the electromagnetic parameters of the antenna, and then the SA is applied to optimize the antenna geometrical parameters to obtain the target value. In order to verify the feasibility and effectiveness of this model, a broadband patch antenna with slots is designed. The sizes and positions of the slots are the input of the ANN, while the return loss of the antenna is the output. By applying the proposed model, the broadband patch antenna with 17.4% relative bandwidth is achieved which proves that the proposed model is feasible.**

***Index Terms*—Broadband patch antenna, artificial neural network, simulated annealing algorithm, optimization.**

I. Introduction

The study of antennas is an important topic in the field of wireless communication, and electromagnetic simulation software can be used to design antennas. However, such antenna design methods usually require sufficient working experience. The design process is not only complicated but also time-consuming, and it is also difficult to achieve an optimal design. With the improvement of antenna performance requirements, the structure of the antenna becomes more complicated and the difficulty of the design is greatly increased. Therefore, the optimal design of the antenna is becoming more and more important. Studies have shown that [1]-[2], antenna optimization design can save a lot of time and energy, and can improve design accuracy. However, a large number of full-wave electromagnetic simulations need to be performed during the design optimization process, which consumes a lot of time. This is a big challenge for the optimal design of the antenna. Therefore, it is very significant to improve the antenna optimization speed without reducing the accuracy greatly. The improved method needs to meet two conditions: first, it can approximate complex nonlinear relationships more accurately; second, it can perform a large number of calculations in a short time.

The artificial neural network (ANN) meets these two points exactly, so it is very suitable for solving the problem of antenna optimization design. It trains and tests the antenna data to ensure that the output is close to the true value. Then, the trained ANN can be applied to replace the electromagnetic simulation software to simulate the antenna, which can not only get accurate results but also speed up the antenna design process. In [3], three machine learning methods were used to optimize antenna design and a dual T-shaped monopole antenna was designed to compare the advantages of these different models and to verify the feasibility. In [4], several antenna arrays were designed to verify the effectiveness of a multi-level neural network model. The frequency was an additional input parameter which would lead to increases in the data set and training time of the neural network. A model using the electromagnetic parameters of the antenna as the input of the neural network and the structural parameters as the output was proposed in [5] which can lead to a non-unique problem, that is, one input will correspond to multiple outputs. To solve this problem, the range of the input data needs to be limited.

In this paper, a novel model combining the ANN with the SA is proposed. The ANN is employed to predict the electromagnetic performance of the antenna and to construct the cost function for the SA, while the SA is used to optimize the antenna to achieve the required solution. Then, a broadband patch antenna is designed to verify the feasibility of the model. To expand the bandwidth of the antenna, some slots are added. The sizes and positions of the slots have a great influence on the bandwidth of the antenna, so they are set as the input of the ANN, while the reflection coefficient of the antenna is the output. After the ANN is trained, the SA is adopted to obtain the suitable sizes and positions of the slots so that the antenna can attain the higher bandwidth. The result shows that the proposed model can achieve a broadband patch antenna with a small number of data set which proves the effectiveness of the model.

II. Theories of the Artificial Neural Network and the Simulated Annealing

In this section, the ANN and the back propagation neural network (BPNN) and the SA are introduced.

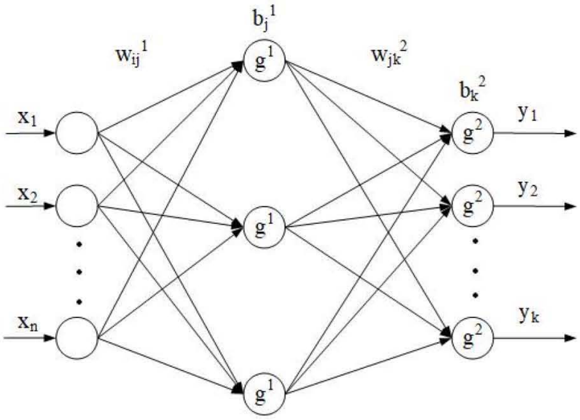

Fig. 1. The structure of a three-layer BPNN.

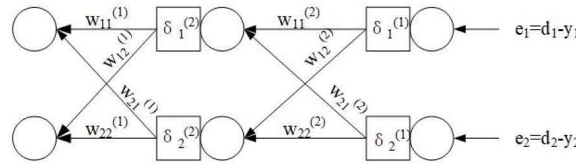

Fig. 2. The back propagation process of error.

A. Artificial Neural Network

The ANN [6-7] is a model that mimics the animal neural networks. It can process information by adjusting the weights and thresholds between layers and has the ability of self-learning and self-adaptation. BPNN [8] is one of the most widely used neural network models. It adopts a multi-layer structure, including an input layer, multiple hidden layers and an output layer while each layer is fully connected. Activation function is used in each hidden layer node of the BPNN. The BPNN has two main processes including forward propagation of signals and back propagation of errors.

The structure of a three-layer BPNN is shown in Fig 1. The process of using the input value to obtain the output value in the network is called forward propagation. The calculation for the forward propagation of the signal is as follows:

$$y_k = g^2\left[w_{jk}^2 g^1\left(w_{ij}^1 x_i - b_j^1\right) - b_k^2\right] \tag{1}$$

where x_i is the input of the network and it is the structural parameter of the antenna, i represents the number of the input neurons; y_k is the output of the network which is the electromagnetic parameter of the antenna, k represents the number of the output neurons; j represents the number of hidden neurons; g^1 is the activation function of the neural network from the input layer to the hidden layer, while g^2 is the activation function between the hidden layer and the output layer; w^1 is the connection weight of the input layer and the hidden layer of the neural network, while w^2 is the weight of the hidden layer and the output layer; b^1 is the threshold of the hidden layer, and b^2 is the threshold of the output layer.

The process in which the error is transmitted backwards through the network is called back propagation of the error. The back propagation process of error is shown in Fig 2. The weights and thresholds of the back propagation process will be updated constantly. The update equations can be expressed as

$$\begin{cases} \Delta w_{ij}^1 = \alpha \delta_j^2 x_i \\ \Delta b_j^1 = \delta_j^2 x_i \end{cases} \tag{2}$$

$$\begin{cases} \Delta w_{jk}^2 = \alpha \delta_k^1 y_k \\ \Delta b_k^2 = \delta_k^1 y_k \end{cases} \tag{3}$$

where α is the learning rate of the ANN, δ_j^2 is the error between the hidden layer and the output layer, while δ_k^1 is the error between the input layer and the hidden layer; Δw_{ij}^1 and Δb_j^1 represent the change of the weight and threshold between the input layer and the hidden layer, while Δw_{jk}^2 and Δb_k^2 are the change of the weight and threshold between the hidden layer and the output layer.

B. Simulated Annealing

The simulated annealing algorithm (SA) [9-10] is an optimization algorithm that is based on the principle of annealing of solids. The advantage includes to assist in finding the global optimal solution in a relatively short time. This algorithm can be applied to many optimization problems, and under the premise of achieving better results, its calculation amount is relatively small. Therefore, the SA is used in the proposed model to optimize the antenna configurations.

III. Proposed Model

The proposed model uses a trained ANN to carry out the simulation of the antenna. The trained ANN can also help to construct the cost function for the SA, and then the SA is employed to find the optimal solution of the antenna. The working flow chart of the proposed model is shown in Fig 3.

The data set from HFSS is applied to train the ANN. The geometrical parameters of the antenna are used as the input variables while the performance of the antenna is the output variable. The training set is employed to train the ANN while the test set is used to evaluate the performance of the ANN. The designed ANN consists of an input layer, three hidden layers and an output layer. The number of neurons a in the hidden layer is evaluated by

$$a = \sqrt{n + m} + p \tag{4}$$

where n is the number of neurons in the input layer, m is the number of neurons in the output layer, and p is a random number in the range of 1 to 10. The performance of the neural network is evaluated by the mean square error which can be computed by

$$\mathrm{MSE}\left(y, y'\right) = \frac{\sum_{i=1}^{n}\left(y_i - y_i'\right)^2}{n} \tag{5}$$

where y is the expected output, y' is the predicted output of the ANN, and n is the number of samples.

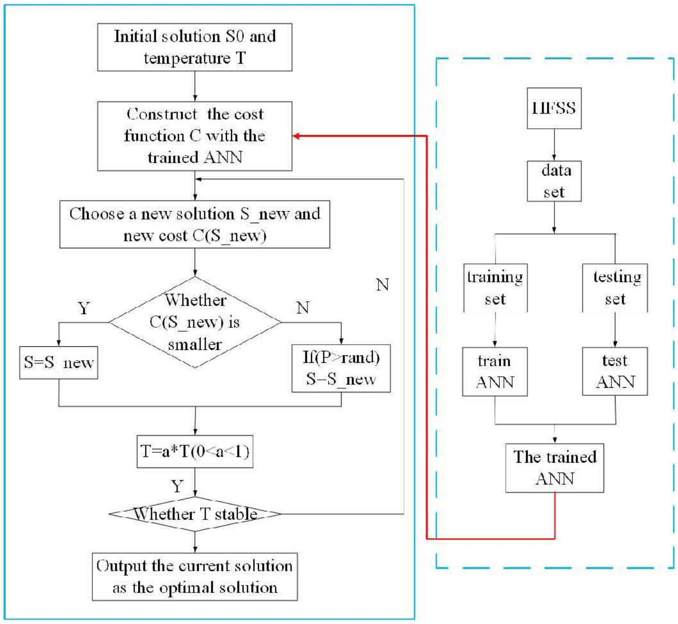

Fig. 3. Flow chart of the proposed model.

TABLE I
DIMENSIONS OF THE ANTENNA

Parameter	Ls	Ws	Lp	Wp	X	R1
Value(mm)	52	52	26	20.8	5.2	1.43
Parameter	R2	coax_r1	coax_r2	h1	h2	h3
Value(mm)	1.3	0.74	0.32	0.508	1.71	3.9

IV. Antenna design

In this section, a broadband patch antenna is designed to verify the effectiveness of the proposed model. The antenna includes 4 slots and its center frequency is considered as 10 GHz. It prints on the Rogers 4003 substrate and the thickness is 0.508 mm. The geometry of the broadband patch antenna is shown in Fig 4, and the dimensions of the antenna are given in Table I.

Slots on the antenna can broaden the bandwidth. Changing the sizes and positions of the slots could affect the bandwidth. So in the training of the ANN, the sizes and positions of the slots are the input while the return loss of the antenna is the output. The length of the vertical slots L1 is set in the range of 1mm to 15mm, the length of the horizontal slots L2 is set in the range of 0.5mm to 5mm, and the ordinate of the slots Y is set in the range of 2mm to 9mm. All possible combinations of these three parameters are applied to create the data set.

The data set involves 125 sets of data among which 110 sets of data are the training set, and 15 sets of data are the testing set. The input layer has 3 neurons and the output layer has 41 neurons. According to (4), a is from 7 to 17. In the proposed model, a is set as 15. The parameters of the ANN are shown in the Table II.

The test result of the ANN is shown in Fig 5, only three curves in the test set are drawn here for simplicity. It can be seen that the error between the output value of the ANN

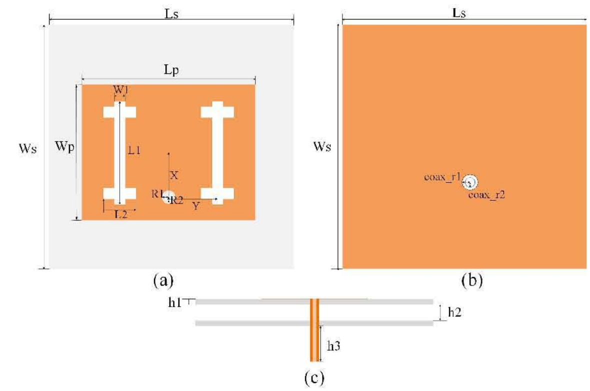

Fig. 4. Geometry of the microstrip patch antenna.(a) Top view. (b) Bottom view. (c) Front view.

TABLE II
PARAMETERS OF THE ANN

Neural Network Parameters	Value
Number of Input Layer Neurons	3
Number of Output Layer Neurons	41
Number of Hidden Layer Neurons	15
Number of Hidden Layers	3
Error Goal	10^{-4}
The Learning Rate	0.001
Number of Epochs	3000

and the value of the testing set is quiet small. Therefore, the ANN can predict the broadband patch antenna effectively and accurately, which can replace the long and complicated electromagnetic simulation process of the full-wave simulation software.

Next, the SA is applied to find the larger bandwidth of the antenna in which the cost function is constructed by the trained ANN. The final value of the L1 is 14.7mm, L2 is 0.6mm and Y is 7.3mm, respectively. The optimal solution is entered into the HFSS whose result is compared with the SA, as shown in Fig 6.

The impedance bandwidth of the proposed model is from 9.05 GHz to 10.95 GHz and reaches a 19.0% of the relative bandwidth, while the result of the HFSS is from 9.20 GHz to 10.95 GHz and achieves a 17.4% of the relative bandwidth. The bandwidth of the HFSS is slightly narrower than the bandwidth of the proposed model. It can be seen that the result of the proposed model agrees well with the result of the HFSS. Finally, the radiation patterns at different frequencies of the antenna are given in Fig 7.

V. Conclusion

A novel model of the antenna design combining the ANN with the SA is proposed in this paper. The ANN is used to predict the performance of the antenna while the SA is applied to optimize the antenna to obtain the target value. The cost function of the SA is constructed by the trained ANN. A broadband patch antenna with slots is designed to verify the feasibility and effectiveness of the proposed model. The

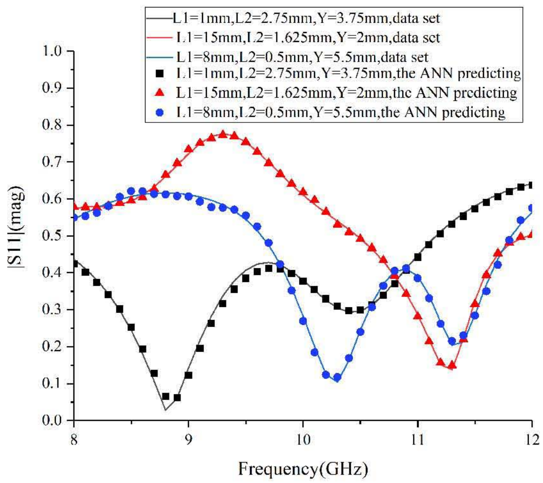

Fig. 5. Test result of the ANN.

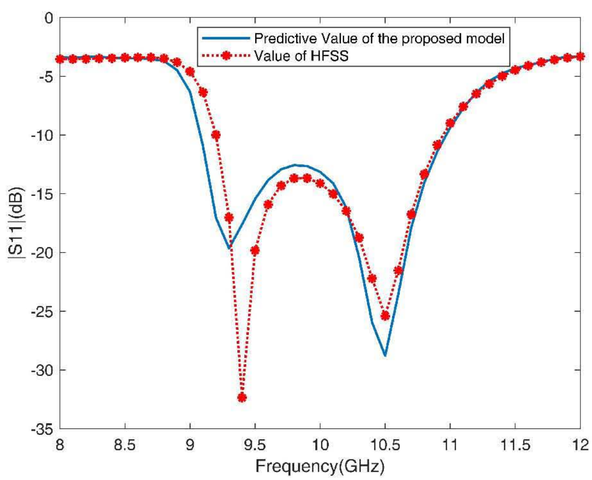

Fig. 6. Results of the proposed model and HFSS.

sizes and positions of the slots are the input of the ANN while the reflection coefficient of the antenna is the output. Finally, the antenna achieves a large bandwidth by using this model. The relative bandwidth of the antenna using the proposed model reaches 19.0% which proves that the proposed model is feasible.

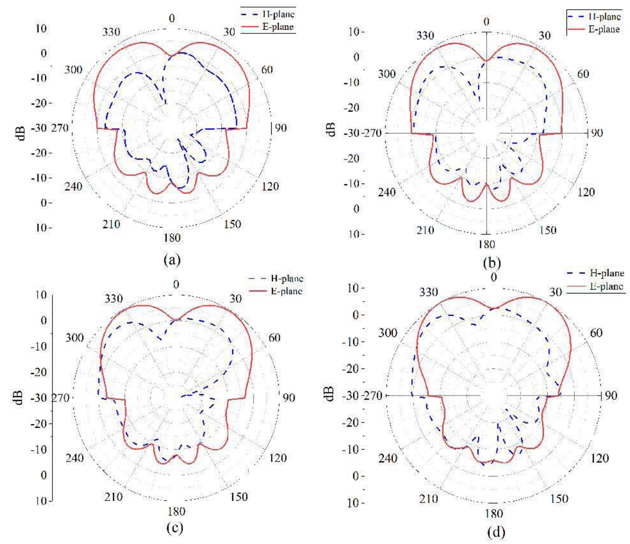

Fig. 7. The radiation patterns of the antenna. (a) Radiation pattern at 9.4 GHz. (b) Radiation pattern at 10 GHz. (c) Radiation pattern at 10.3 GHz. (d) Radiation pattern at 10.8 GHz.

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