

Received August 14, 2021, accepted September 7, 2021, date of publication September 10, 2021, date of current version September 20, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3111902

# Design of UWB Antenna Based on Improved Deep Belief Network and Extreme Learning Machine Surrogate Models

JINGCHANG NAN<sup>1</sup>, HUAN XIE<sup>1</sup>, MINGMING GAO<sup>1,2</sup>, YANG SONG<sup>1</sup>, AND WENDONG YANG<sup>1</sup>

<sup>1</sup>School of Electronic and Information Engineering, Liaoning Technical University, Huludao 125100, China

<sup>2</sup>School of Information Science and Technology, Dalian Maritime University, Dalian 116026, China

Corresponding author: Huan Xie (1875251604@qq.com)

This work was supported in part by the National Natural Science Foundation of China General Program under Grant 61971210.


**ABSTRACT** In the design of conventional microwave devices, the parameters need to be continuously optimized to meet the desired targets, and the whole process is time-consuming and laborious. As a surrogate model, machine learning is an effective optimization method. However, in the modeling process, the high-dimensional data processing and the complex nonlinear relationship between parameters is a problem to be solved. This paper proposes a deep learning model for designing UWB antennas, which determines the model structure of deep belief network (DBN) by particle swarm algorithm (PSO), and then combines DBN and extreme learning machine (ELM). The proposed model can obtain higher feature learning capability and nonlinear function approximation capability, and has been applied to the optimal design of the whole structure of the fractal antenna and the notch structure of the MIMO antenna, and its S-parameters are well fitted while meeting the requirements of the design targets. The DBN-ELM method obtains the good results when compared with common modeling methods using the same training samples (the root mean square error tested is 11.87% in the fractal antenna and 3.56% in the MIMO antenna). Overall, the proposed DBN-ELM model has higher predictive and generalization capabilities, which can also be used to model more complex antenna structures.

**INDEX TERMS** Deep belief network (DBN), extreme learning machine (ELM), particle swarm optimization (PSO), UWB antenna.

## I. INTRODUCTION

At present, the design and analysis methods of traditional antenna use Computer Aided Design (CAD), such as Computer Simulation Technology (CST), High Frequency Structure Simulator (HFSS), etc. Once the antenna parameters are changed, it needs to be simulated again, which leads to the increase of design time and difficulty. The relationship between the geometric and electrical parameters of microwave devices is a combination of linear and nonlinear, such as the relationship between dimensional parameters and working frequency, return loss, radiation pattern and other parameters [1]. Due to complex internal relationships, when the design capabilities of microwave devices increase, it makes the design process more complex and the computational cost increases significantly. Building surrogate

models is an efficient and feasible approach in microwave device design [2], [3]. The EM-based surrogate models allow the evaluation of the operating performance of microwave devices. The surrogate model building process is usually simple and reliable, avoiding repeated calls to EM simulation software and reducing design time. Deep neural networks turned out to be a promising method for solve complex computing problems [4]–[6]. As the research progresses, deep learning has good advantages in handling large amount of, high-dimensional, nonlinear data and has effective applications in optimizing microwave device design [7]–[11]. In the reference [10], a PSO-CNN model combining particle swarm algorithm (PSO) and convolutional neural network (CNN) was proposed to apply the PSO-CNN model to the optimal design of fragmented antennas and obtained good optimization results. In the reference [12], an improved multilayer perceptron (M2LP) model, which is an equivalent convolutional neural network (CNN) model of a standard multilayer

The associate editor coordinating the review of this manuscript and approving it for publication was Raghvendra Kumar Chaudhary .

perceptron (MLP), is proposed, and the model is applied to the prediction of scattering parameters of capacitively fed antennas, showing that the M2LP model can be used as an efficient and reliable regression model for the optimal design of antennas. This indicates that deep neural networks have higher accuracy compared to traditional shallow neural networks in microwave device modeling problems.

Deep Belief Network (DBN) have a strong feature learning capability, which makes classification or prediction easier by converting from low-level feature combinations to high-level abstract representations [13]–[15]. DBNs have been developed and used in many fields, such as in acoustic modeling [14], medical classification [16] *et al.* In reference [8], the Bayesian regularized deep belief network (R-DBN) was first proposed and applied to the extraction of coupling matrix, providing a new solution for inverse filter modeling. However, Bayesian optimization algorithms have a low number of iterations in optimizing hyperparameters and can easily fall into local optimization [17]. In reference [18], a PSO-DBN-based model is proposed to improve the accuracy and analysis efficiency of the model by adaptively adjusting the DBN model parameters through PSO. However, it is easy to hide the number of layers too much, which causes overfitting problem. In reference [19], researchers conducted numerous experiments showing that multiple hidden layers outperform a single hidden layer. Unfortunately, the number of nodes in the DBN's hidden layer is not easy to determine. The algorithm has the advantages of easy implementation and fast convergence, and can obtain the global optimal solution [20]. The PSO algorithm is widely used in antenna design [21]. In reference [22], the Ramped Convergence Particle Swarm Optimization (RCPSO) algorithm, using the Heterogeneous boundary conditions to search, achieve the design requirements while reducing the overall antenna size. In reference [23], PSO is conceptually added to a bias of the antenna design, and different methods are adopted to deal with constraint conflicts to optimize the rectangular ground, which increases the working bandwidth of the antenna. Therefore, PSO algorithm is used to optimize the model structure of DBN and determine the optimal number of nodes in the hidden layer [24].

In order to improve the antenna design efficiency and antenna design within feasible design parameters, accurate and reliable models are needed for optimization. Applying DBN to antenna design can solve the complex nonlinear problems with high-dimensional parameters and reduce the time to optimize the design. In the training process of DBN, each layer of restricted Boltzmann machine (RBM) is first trained by unsupervised greedy training, and the trained RBMs are combined to construct DBN, and then the whole network is fine-tuned by traditional global optimization algorithm to make the network optimal. However, The global optimization algorithm based on gradient cannot train deep neural network well because of the shortcoming that get into local optimality and global fine-tuning need a long time. Adding the extreme learning machine (ELM) to the training process of the DBN

can enhance the prediction accuracy of the model and the model performance [25].

In the study, an improved deep belief network-extreme learning machine (DBN-ELM) model based on PSO optimization is proposed in order to realize a high-precision and fast antenna model for optimal design, which has been applied to the optimal design of UWB antennas. Test samples are selected for prediction with the proposed model, and the predicted S-parameters are compared with those of the simulation software to demonstrate the feasibility of the method. In Section 2, the proposed DBN-ELM model is introduced, the number of hidden neurons in DBN is determined by PSO algorithm, and then the feature output extracted by the improved DBN is used as the input of ELM to increase efficiency of the whole model. In Section 3, the proposed model is used to optimize the design of the UWB antennas. To verify the correctness of the method, an experimental model of a fractal antenna and a Multiple-input-multiple-output (MIMO) antenna with notch characteristics is designed and tested. Finally, it ends with the brief conclusion of Section 4.

## II. IMPROVED DBN-ELM MODEL

This section describes the proposed improved DBN-ELM model. It mainly includes two parts. The first part introduces the improved DBN model, using PSO algorithm to optimize the number of hidden layer nodes of DBN, so as to obtain the best network structure. The second part introduces the model structure and training method of DBN-ELM.

### A. STRUCTURE OF THE PROPOSED DBN – ELM MODEL

The DBN is a generative model that consists of multiple RBMs, in which the entire neural network generates training data according to the maximum probability by training the weights among its neurons. During the training process, each restricted Boltzmann machine network is trained layer by layer from top to bottom, and get the original data in the process of unsupervised learning of low-dimensional. The dimensionality of the data is reduced while preserving the key features of the data.

In this paper, an  $n$ -layer DBN is adopted, including an input layer and  $n - 1$  hidden layers, and  $n - 1$  RBMs are obtained through greedy training. The output of the  $n - 1$  RBMs is taken as the input of ELM, DBN and ELM are combined into the overall model. Its network structure is shown in Fig. 1.

Assuming that the  $n$ th hidden layer has  $N$  nodes and the  $n - 1$ th hidden layer has  $m$  nodes, define  $y_i$  as the output of the entire model, expressed as,

$$y_j = \sum_{i=1}^N \beta_i g(\mathbf{W}_i \mathbf{H}_{n-i} + \mathbf{b}_i), \quad j = 1, \dots, m \quad (1)$$

where,  $\mathbf{W}_i$  is the weight from the  $n - 1$ th hidden layer to the  $n$ th hidden layer,  $\mathbf{b}_i$  is the bias from the  $n - 1$ th hidden layer to the  $n$ th hidden layer,  $\beta_i$  is the output weight from the  $n$ th hidden layer to the output layer. Then  $\{\mathbf{W}_i, \mathbf{b}_i\}$  is determined by ELM [26].  $g(X)$  is the activation function. Where,  $\mathbf{H}_n$  is

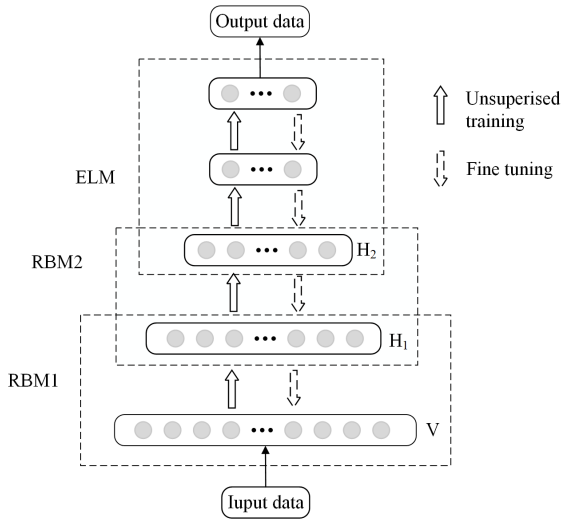


FIGURE 1. Network structure of DBN-ELM.

the output from the  $n - 1$ th layer to the  $n$ th layer of DBN, expressed as,

$$H_n = \begin{bmatrix} g(W_1 H_{n-1,1} + b_1) \cdots g(W_N H_{n-1,1} + b_N) \\ g(W_1 H_{n-1,m} + b_1) \cdots g(W_N H_{n-1,m} + b_N) \end{bmatrix} \quad (2)$$

$$g(X) = \frac{1}{1 + e^{-X}} \quad (3)$$

$E$  is the root mean square error function of the network, the error between the target output  $T$  and the model predicted output  $Y$  is calculated,  $N$  is the number of training samples, and the error should be minimized in the optimization process, expressed as,

$$E = \sqrt{\frac{1}{N} \sum_{i=1}^N (T_i - Y_i)^2} \quad (4)$$

**B. PARAMETER OPTIMIZATION BASED ON PSO ALGORITHM**

The flowchart of the PSO to optimize the DBN-ELM model is shown in Fig. 2. The optimization steps are given below.

Step 1: Sample data preparation. The extracted data is divided into 80% training set and 20% test set.

Step 2: PSO algorithm optimization DBN. Randomly initialize the parameters of the RBMs to establish the RBMs. In the training process, particle optimization is carried out through PSO, and the optimal particle position corresponding to the final number of DBN hidden layers  $\{N, m\}$  is output, and then the optimized DBN model is obtained [27]. In the optimization process, the average accuracy of cross-validation of test samples was selected as the fitness function.

Step 3: The features of the pre-trained DBN outputs are trained by using ELM, and the parameters of the model are fine-tuned to improve the model performance by calculating the output error of the training samples.

Step 4: Output prediction data and test error.

**III. CASES STUDY**

With the rapid development of wireless communication system, the base station equipment tends to be more and more miniaturized, which means the size of antenna should be smaller and smaller, and the UWB antenna is mostly used in small base stations, and its size should be reduced. As the working performance of UWB antenna is improved, the design process is required to be more intelligent and efficient. The deep learning algorithm also becomes an effective method to optimize the design of antenna structure. In this paper, an improved DBN-ELM model is proposed which can be used for fast, accurate and high performance antenna modeling. In this section, firstly, the design parameters of the optimized antenna are introduced. Then the design parameters of the proposed model and the simulation results of the optimized antenna are presented. Based on this, the performance comparison of the improved DBN-ELM model with the conventional algorithm is also given to demonstrate the proposed modeling method and experimental results.

HFSS-MATLAB-Api [28] is a library function in MATLAB software, which can be used to generate scripts and control the HFSS software through the script interface to generate 3D models and analyze and solve them, and finally output simulation results. The optimization design of microwave devices can be done independently in MATLAB, and the solution and simulation process is also done automatically by MATLAB calling HFSS. In our proposed modeling method, the data exchange between MATLAB software and HFSS software is implemented in VB Script language to obtain the training samples more efficiently and automatically. Firstly, the antenna size parameters are changed in MATLAB, and then the script of HFSS is called to simulate in the electromagnetic simulation software HFSS to get the training samples. finally, the trained DBN-ELM model can be used for the optimization design of the antenna.

**A. OPTIMIZED DESIGN OF FRACTAL ANTENNA**

Fractal antenna is a kind of small multi-band antenna, which can make the antenna resonate in multiple frequency bands due to its self-similarity property. The overall structure size and scale factor determine the multiple frequencies at which the fractal antenna works. In some fractal structures, the multi-band of the fractal antenna is controlled by properly adjusting the scale factor [29], [30]. The optimized first UWB antenna is a fractal antenna, the overall size is 28.15mm × 28.4mm × 1.6mm. The radiation patch of the antenna adopts the 4th order fractal structure and excises the local upper triangle of the octagonal snowflake structure, which can further reduce the antenna size, while the 50 microstrip line is used for feed. In addition, the back of the antenna has a rectangular slot in the middle and upper part of the ground plate, and the left and right corners of the ground plate are cut off to improve the impedance matching characteristics of the improved snowflake fractal antenna, which can extend the antenna bandwidth and further improve the antenna performance. The overall schematic diagram of

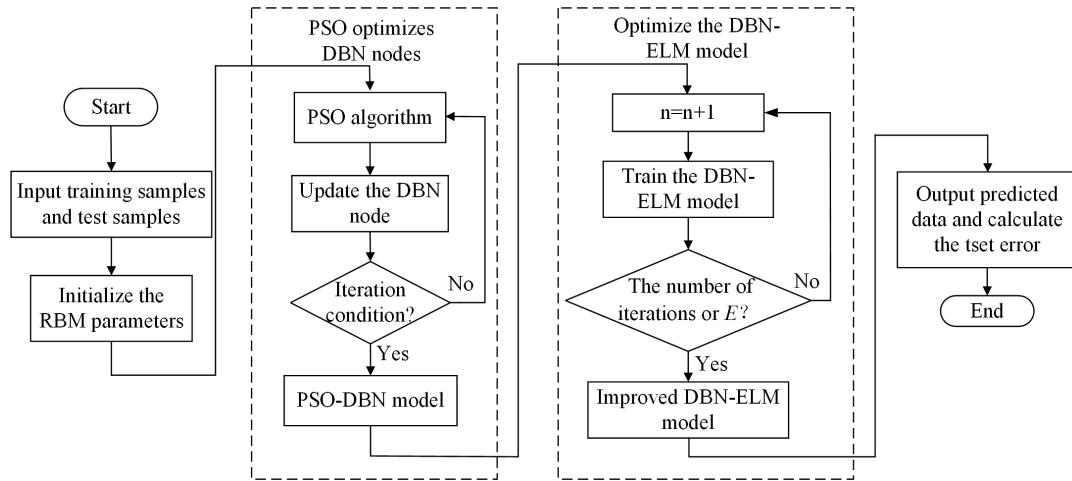


FIGURE 2. Flowchart of DBN-ELM model optimized by PSO algorithm.

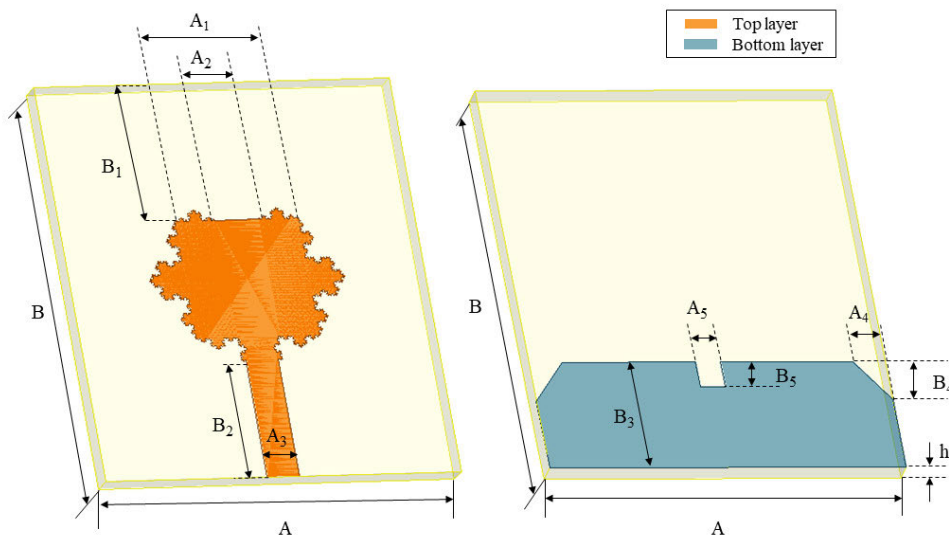


FIGURE 3. Schematic diagram of the fractal antenna.

TABLE 1. Optimal dimension parameters of fractal antenna.

Parameters	Data range/mm	Parameters	Data range/mm
$A_1$	9–12	$B_1$	6–8
$A_2$	3–4	$B_2$	5–10
$A_3$	2–4	$B_3$	8.5–10.5
$A_4$	2–4	$B_4$	2–4
$A_5$	1.5–4.5	$B_5$	1–4

the fractal antenna is shown in Fig. 3, the left side is the top layer and the right side is the bottom layer. The design index of the antenna is to cover the operating band of 3.3-12GHz, and  $S_{11}$  is less than  $-10\text{dB}$ . In antenna design,  $S_{11}$  is the key parameter that impacts the radiation characteristics of the antenna. If a good radiation characteristic is achieved, the antenna will also get a high gain.

Ten dimensional parameters of this antenna are used as optimization variables and randomly combined as input data for the improved DBN-ELM model with the specific

parameters shown in Table 1. Randomly combined into 200 groups of different antenna parameters as training inputs, with 10 parameters in each group. The simulation is invoked by HFSS through a VB Script, and each set of antenna size parameters input has the corresponding S-parameters as output samples. Through the experiment, the HFSS simulation results in the time of 88.17 seconds for one set of samples.

The model parameters are very critical to the experimental results, as studies have shown that the model structure, number of iterations, learning rate, and number of input samples have a significant impact on the performance. Through experiments, the number of hidden layer nodes optimized by PSO algorithm is 40 and 32, respectively, and the particle dimension is 2, and the number of hidden layers is 2. Fig. 4 shows the RMSE of the PSO algorithm with different number of iterations. It can be seen that the test error of the model reaches  $1e-05$  at 53 iterations, and the training error of the model reaches  $1e-05$  at 66 iterations, satisfying the termination condition.

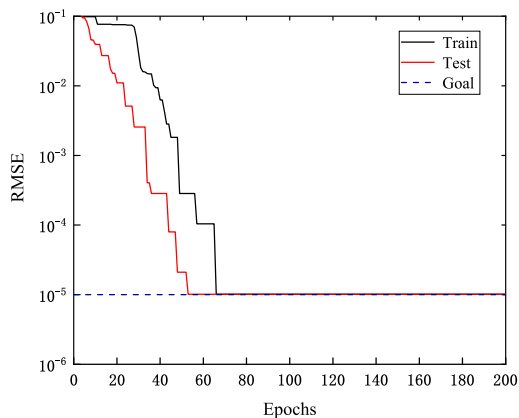


FIGURE 4. Flowchart of DBN-ELM model optimized by PSO algorithm.

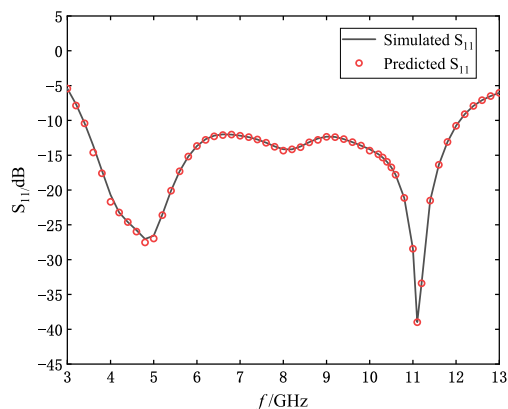


FIGURE 5.  $S_{11}$  simulation results of the optimized fractal antenna.

The optimal parameters of the model are set as follows: 110-40-32-10, with a learning rate of 0.001 and the number of iterations of 200 until the results converge. The completed antenna size parameters in this paper are shown in Table 2, and Fig. 5 compares  $S_{11}$  and HFSS simulation results predicted by the method proposed in this paper. As can be seen from Fig. 5, the antenna is designed to operate in a frequency range of 3.2 to 12GHz, and the actual simulation results show that the frequency response in the range of 3.3 to 12.1 GHz is less than  $-10$  dB. With the increase of the fractal order, the minimum operating frequency decreases gradually. When the order reaches 4, the antenna has two resonant frequency point, and the values  $S_{11}$  are all below  $-20$ dB. Because of the good resonance characteristics, the bandwidth of the antenna can be broadened, and the absolute bandwidth can basically cover the working band range of UWB communication system. Due to the basically fitting curve of HFSS simulation results and the curve of prediction results of the proposed method in Fig. 5, it shows that the proposed model has high accuracy and can replace the HFSS simulation.

For the discrete frequency points of 3.4GHz, 6.85GHz and 8.8GHz, respectively, view the radiation pattern of the antenna, as shown in Fig. 6. It can be seen that the radiation pattern of the antenna's E-plane is bidirectional, and a '8' shape with good radiation front and rear flaps appears. The radiation pattern of the H-plane is omnidirectional, indicating that the antenna has good radiation characteristics. However,

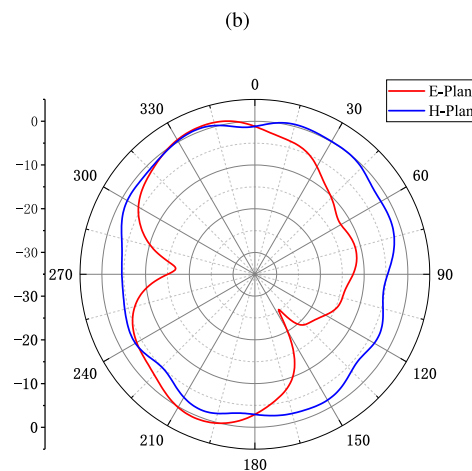
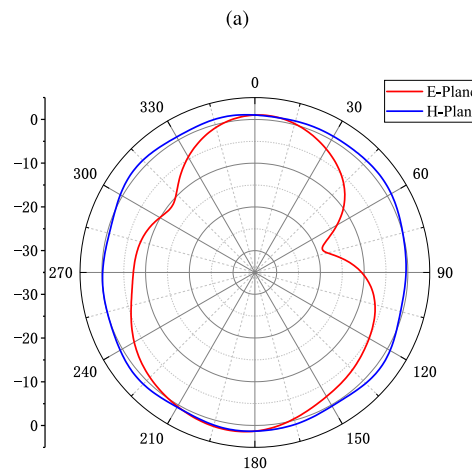
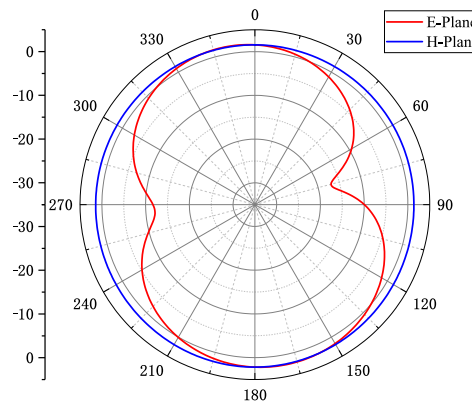


FIGURE 6. Radiation patterns of the fractal antenna at discrete frequencies of (a) 3.3 GHz, (b) 6.85 GHz and (c) 8.8 GHz.

at the higher 8.8GHz, more electromagnetic waves will be radiated due to the finite rectangular ground contact, which makes the radiation flap slightly distorted, resulting in the antenna radiation omnidirectional characteristic is not as good as the low frequency band effect.

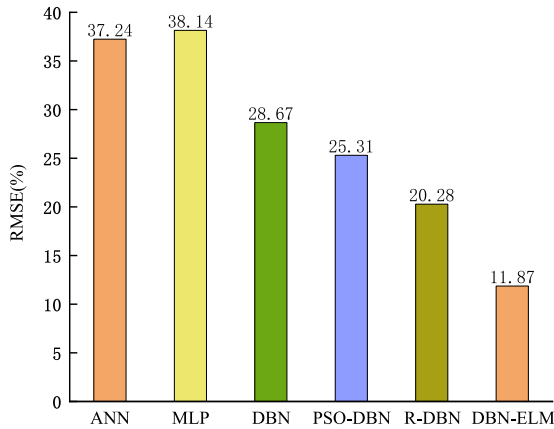


FIGURE 7. RMSE of the fractal antenna.

The performance comparisons of ANN, MLP, DBN and PSO optimized DBN-ELM for fractal antennas are shown in Table 3 and Fig.7. It can be seen from Fig. 7 that the RMSE of DBN-ELM is the smallest among the four methods, which is 11.87%. After calculation, the prediction accuracy of DBN-ELM is 68.13% better than the ANN, 68.88% better than the MLP, and 58.60% better than the DBN, 53.10% better than the PSO-DBN and 41.47% better than the R-DBN. It can be seen that the DBN-ELM model optimized by PSO has high prediction accuracy. In this experiment, the total computation time for 200 sets of samples is 17,634 seconds, which is less than 5 hours. Compared with the conventional HFSS design process, the method in this paper is more simple and fast. In addition, compared with the results in the M2LP model [12], the proposed method can process more training data after fewer unsupervised learning iterations.

TABLE 2. Optimal dimension parameters of fractal antenna.

Parameters	Data range/mm	Parameters	Data range/mm
$A$	28.4	$B$	28.15
$A_1$	9.86	$B_1$	7.41
$A_2$	3.29	$B_2$	8.54
$A_3$	2.56	$B_3$	9.28
$A_4$	2.62	$B_4$	3.39
$A_5$	2.16	$B_5$	2
$t$	1.6		

TABLE 3. Comparison of results of different methods for the fractal antenna.

Methods	Test MAE	Test RMSE
ANN	1.82%	37.24%
MLP	2.1%	38.14%
DBN	1.32%	28.67%
MLP	2.1%	38.14%
PSO-DBN	1.14%	25.31%
R-DBN	0.957%	20.28%
DBN-ELM	0.174%	11.87%

B. OPTIMAL DESIGN OF NOTCH MIMO ANTENNA

MIMO antennas are simple and compact, good port isolation and other good performance indicators. MIMO technology is widely used in multi-standard mobile/wireless systems [31]. The optimized second antenna structure is the MIMO antenna, the schematic diagram is shown in Fig. 8, the top layer is shown on the left and the bottom layer is

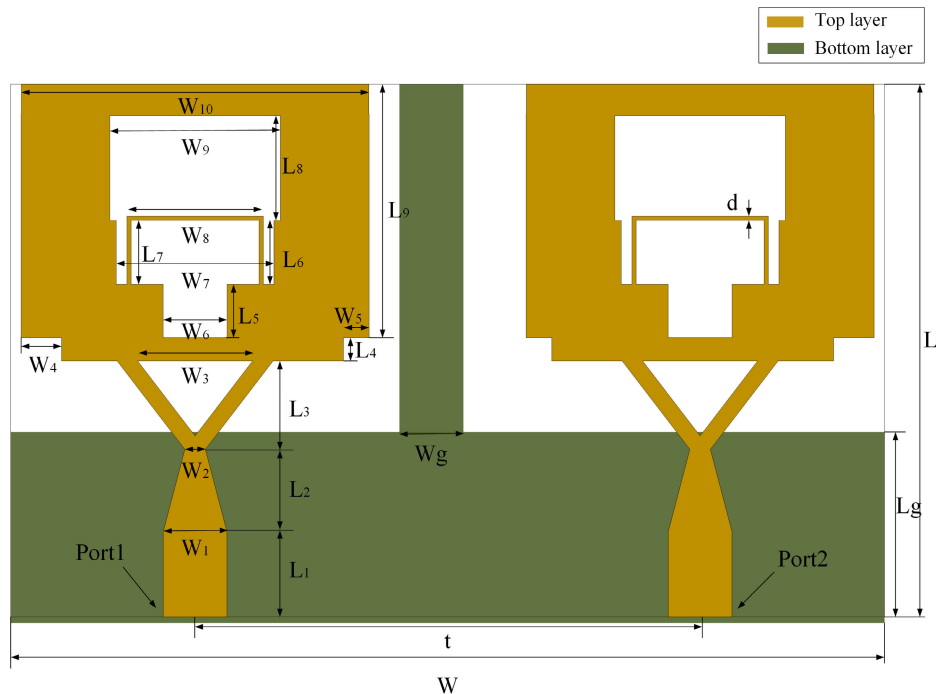


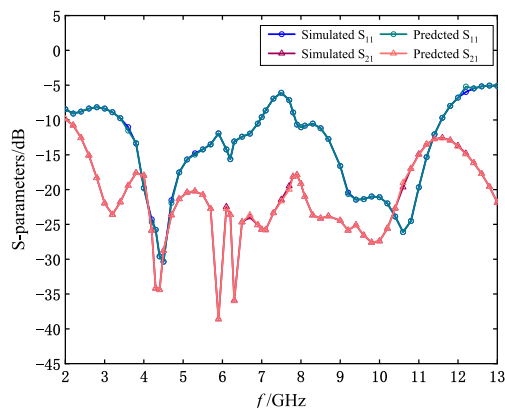
FIGURE 8. Schematic diagram of the MIMO antenna.

**TABLE 4. Optimal dimensional parameters of the MIMO antenna.**

Parameters	Data range/mm
$L_7$	2–5
$W_8$	5.2–7.2
$d$	0.1–1

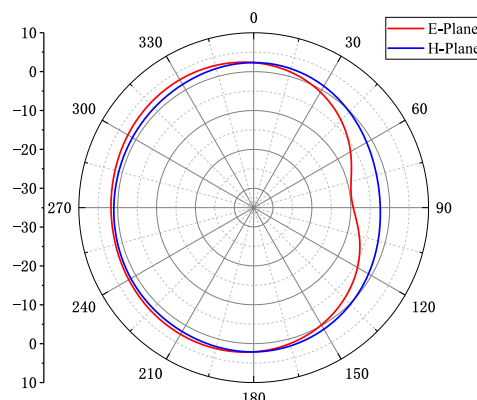
**TABLE 5. Structural parameters of the optimized MIMO antenna.**

Parameters	Data range/mm	Parameters	Data range/mm
$L$	25.0	$W$	41.0
$L_1$	4.00	$W_1$	3.00
$L_2$	3.86	$W_2$	1.00
$L_3$	4.14	$W_3$	5.40
$L_4$	1.10	$W_4$	1.90
$L_5$	2.50	$W_5$	1.20
$L_6$	3.00	$W_6$	3.00
$L_7$	3.00	$W_7$	7.40
$L_8$	4.90	$W_8$	6.40
$L_9$	11.9	$W_9$	8.00
$L_g$	8.50	$W_{10}$	16.3
$t$	23.7	$W_g$	2.00
$d$	1.60		

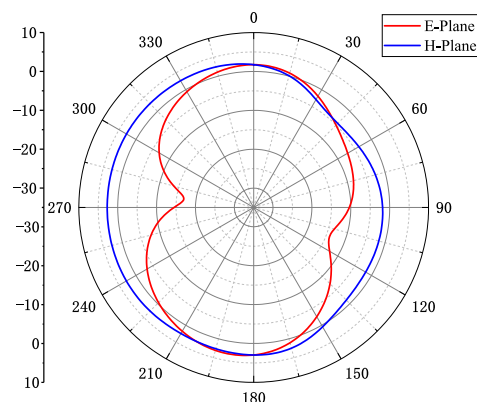


**FIGURE 9. Simulation results of S-parameters of optimized MIMO antenna.**

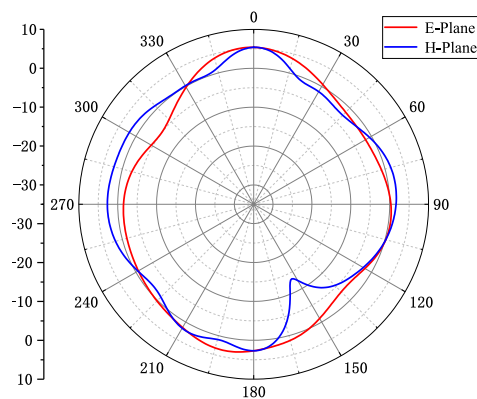
shown on the right. The size of the antenna is  $41\text{mm} \times 25\text{mm} \times 1.6\text{mm}$ , and the bandwidth of the antenna is widened by a wrench-shaped microstrip feed line, and a rectangular structure is introduced in the ground plane of the antenna to obtain a good port isolation. The design objectives of the antenna are: the operating frequency is 3.1–12.0 GHz, and  $S_{11}$  is less than  $-10\text{dB}$ , and  $S_{21}$  is more than  $-15\text{ dB}$  in the whole operating frequency. In order to suppress the interference in the downlink band of X-band (7.25–7.75GHz) and realize the notch characteristics of the MIMO antenna, C-shaped branches are introduced on the antenna radiator, and by adjusting the size of the notch structure and its position are used to determine the frequency range to be suppressed. The proposed DBN-ELM model can accurately predict the size of the C-shaped dendrites (for  $L_7$ ,  $W_8$  and  $d$



(a)



(b)



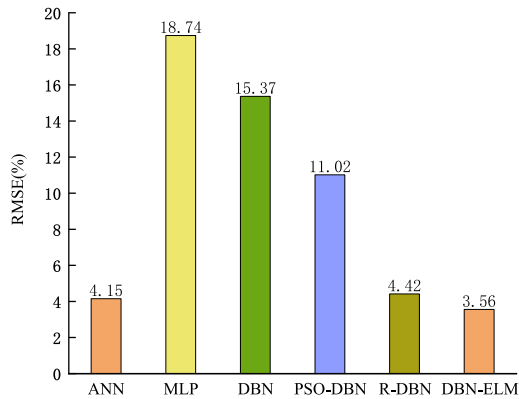
(c)

**FIGURE 10. Radiation patterns of MIMO antenna at discrete frequencies of (a) 4.2GHz, (b) 6.2GHz and (c) 8.2GHz.**

in Fig. 8). Similarly, 500 sets of data in Table 4 are prepared as training input samples, and the corresponding S-parameters are calculated by HFSS simulation software simulation as training output samples. The sample acquisition process took 25,620 seconds. The 500 sets of training data are substituted

**TABLE 6.** Comparison of results of different methods for the MIMO antenna.

Methods	Test MAE	Test RMSE
ANN	0.46%	4.15%
MLP	1.16%	18.74%
DBN	1.05%	15.37%
PSO-DBN	0.82%	11.02%
R-DBN	0.53%	4.42%
DBN-ELM	0.21%	3.56%

**FIGURE 11.** RMSE of the MIMO antenna.

into the DBN-ELM model for training to find the antenna size that best meets the design requirements.

The DBN-ELM model structure is defined as 120-28-26-3. The dimensional parameters of the optimized MIMO antenna are shown in Table 5, and the comparison of the predicted S-parameters of the DBN-ELM model and the HFSS simulation results are shown in Fig. 9. It can be seen from the figure that the antenna produces a notch band from 6.9 to 7.9 GHz after adding the predicted notch structure, which effectively suppresses the interference in the downlink band of satellite X-band from 7.25 to 7.75 GHz. In addition,  $S_{21}$  is higher than  $-15$  dB from 2.8 to 13 GHz. Because the prediction of DBN-ELM model is basically consistent with the simulation results of HFSS, so the proposed method can replace HFSS in antenna design. Fig. 10 shows the radiation pattern of the MIMO antenna measured on the E-plane and H-plane at different frequencies of 4.2 GHz, 6.2 GHz and 8.2 GHz. The above results show that the optimized MIMO antenna is simple, compact, and has good port isolation performance. The antenna structure designed in this paper is more complex compared to the literature [32], which indicates that this method can be applied to more complex model structures.

A comparison of the different model optimization results for the MIMO antenna is shown in Table 6 and Fig. 11. According to Fig. 11, the RMSE of DBN-ELM is 3.56%. Its prediction accuracy is 14.2% better than the ANN, 81.00% better than the MLP, and 76.84% better than the DBN, 67.67% better than the POS-DBN and 19.46% better than the R-DBN. It can be concluded that DBN-ELM has better prediction capability.

#### IV. CONCLUSION

To address the time-consuming and laborious issue of designing microwave devices by traditional electromagnetic simulation software, this paper proposes a DBN-ELM model based on PSO optimization. The model can quickly extract samples, reduce the complexity and computational cost caused by repeated simulations in the design process of antennas, and greatly improve the efficiency of antenna design. In the experiment, two UWB antenna structures are optimized through this model: (1) The working frequency band of the fractal antenna is 3.3-12.1GHz, and  $S_{11}$  is less than  $-10$ dB; (2) The working frequency band of the MIMO antenna with notch characteristics is 3.1-12.0 GHz, and  $S_{11}$  is less than  $-10$ dB, and the isolation degree is more than 15 dB. Using the model to optimize the C-shaped stubs introduced on the radiation patch to suppress the interference of the X satellite downlink communication frequency band (7.25-7.75GHz). The experimental results show that the proposed model has good fitting accuracy for the S-parameters of the above antenna compared with the traditional simulation software HFSS, which proves the feasibility of the method. In terms of model performance, the prediction accuracy of the proposed DBN-ELM is higher than that of other surrogate models, with stronger reliability and better prediction capability.

In the experiment, the model considers only a two-layer structure, and in the case of satisfying a certain accuracy, can quickly achieve a good optimization results. However, in order to design an antenna with better working performance, further research is needed to improve the applicability of the method. In summary, the proposed DBN-ELM model can effectively replace the conventional electromagnetic simulation software, providing a new solution for designing antennas.

#### REFERENCES

- [1] A. Suintives, M. S. Hossain, J. Ma, R. Mitra, and V. Veremey, "Application of artificial neural network models to linear and nonlinear RF circuit modeling," *Int. J. RF Microw. Comput.-Aided Eng.*, vol. 11, no. 4, pp. 231–247, Jul. 2001.
- [2] C. Zhang, J. Jin, W. Na, Q. J. Zhang, and M. Yu, "Multivalued neural network inverse modeling and applications to microwave filters," *IEEE Trans. Microw. Theory Techn.*, vol. 66, no. 8, pp. 3781–3797, Aug. 2018.
- [3] B. Liu, H. Yang, and M. J. Lancaster, "Global optimization of microwave filters based on a surrogate model-assisted evolutionary algorithm," *IEEE Trans. Microw. Theory Techn.*, vol. 65, no. 6, pp. 1976–1985, Jun. 2017.
- [4] Z. Wei, D. Liu, and X. Chen, "Dominant-current deep learning scheme for electrical impedance tomography," *IEEE Trans. Biomed. Eng.*, vol. 66, no. 9, pp. 2546–2555, Sep. 2019.
- [5] M. Zeng, L. T. Nguyen, B. Yu, O. J. Mengschoel, J. Zhu, P. Wu, and J. Zhang, "Convolutional neural networks for human activity recognition using mobile sensors," in *Proc. 6th Int. Conf. Mobile Comput., Appl. Services (MobiCASE)*, Austin, TX, USA, Jan. 2015, pp. 197–205.
- [6] J. Snoek, H. Larochelle, and R. P. Adams, "Practical Bayesian optimization of machine learning algorithms," in *Proc. Adv. Neural Inf. Process. Syst.*, vol. 4, 2012, pp. 1–9.
- [7] J. Jin, C. Zhang, F. Feng, W. Na, J. Ma, and Q.-J. Zhang, "Deep neural network technique for high-dimensional microwave modeling and applications to parameter extraction of microwave filters," *IEEE Trans. Microw. Theory Techn.*, vol. 67, no. 10, pp. 4140–4155, Oct. 2019.
- [8] G. Pan, Y. Wu, M. Yu, L. Fu, and H. Li, "Inverse modeling for filters using a regularized deep neural network approach," *IEEE Microw. Wireless Compon. Lett.*, vol. 30, no. 5, pp. 457–460, Apr. 2020.



[9] X.-Y. Zhang, Y.-B. Tian, and X. Zheng, "Antenna optimization design based on deep Gaussian process model," *Int. J. Antennas Propag.*, vol. 2020, pp. 1–10, Nov. 2020.

[10] X. Zhang, Y. Tian, and X. Zheng, "Optimal design of fragment-type antenna structure based on PSO-CNN," in *Proc. Int. Appl. Comput. Electromagn. Soc. Symp. (ACES)*, 2019, pp. 1–2.

[11] J. Jin, F. Feng, J. Zhang, S. Yan, W. Na, and Q. Zhang, "A novel deep neural network topology for parametric modeling of passive microwave components," *IEEE Access*, vol. 8, pp. 82273–82285, May 2020.

[12] N. Calik, M. A. Belen, and P. Mahouti, "Deep learning base modified MLP model for precise scattering parameter prediction of capacitive feed antenna," *Int. J. Numer. Model., Electron. Netw., Devices Fields*, vol. 33, no. 2, p. e2682, Sep. 2019.

[13] G. E. Hinton, S. Osindero, and Y.-W. Teh, "A fast learning algorithm for deep belief nets," *Neural Comput.*, vol. 18, no. 7, pp. 1527–1554, Jul. 2006.

[14] A.-R. Mohamed, G. E. Dahl, and G. Hinton, "Acoustic modeling using deep belief networks," *IEEE Trans. Audio, Speech, Language Process.*, vol. 20, no. 1, pp. 14–22, Jan. 2012.

[15] A. R. Mohamed and G. G. D. Hinton, "Deep belief networks for phone recognition," in *Proc. NIPS*, 2010, p. 39.

[16] A. M. Abdel-Zaher and A. M. Eldeib, "Acoustic modeling using deep belief networks," *Expert Syst. Appl.*, no. 46, pp. 139–144, 2016.

[17] E. Choi, S. Chae, and J. Kim, "Machine learning-based fast banknote serial number recognition using knowledge distillation and Bayesian optimization," *Sensors*, vol. 19, no. 19, p. 4218, Sep. 2019.

[18] H. Shan, Y. Sun, W. Zhang, A. Kudreyko, and L. Ren, "Reliability analysis of power distribution network based on PSO-DBN," *IEEE Access*, vol. 8, pp. 224884–224894, Jul. 2020.

[19] F. Yan, J. Jia, Y. Hu, Q. Guo, and H. Zhu, "Smart fire evacuation service based on Internet of Things computing for Web3D," *IEEE Access*, vol. 20, no. 2, pp. 521–532, 2019.

[20] J. Kennedy, "Particle swarm optimization," in *Proc. IEEE Int. Conf. Neural Netw. Nanjing, China: Nanjing Univ. Posts and Telecommunications*, 2019, pp. 1942–1948.

[21] W.-B. Wang, Q. Y. Feng, and D. Liu, "Application of chaotic particle swarm optimization algorithm to pattern synthesis of antenna arrays," *Prog. Electromagn. Res.*, vol. 115, pp. 173–189, Jan. 2011.

[22] M. Samsuzzaman, M. T. Islam, S. Kibria, and M. Cho, "A compact circularly polarized high gain S-band nanosatellite antenna using ramped convergence particle swarm optimization," *Microw. Opt. Technol. Lett.*, vol. 57, no. 6, pp. 1503–1508, Jun. 2015.

[23] S. Kibria, M. T. Islam, and R. Azim, "A heuristic approach to design broadband microstrip patch antenna," in *Proc. IIEEJ Image Electron. Vis. Comput. Workshop*, vol. 6, 2015, pp. 1–4.

[24] Y. Xie, J. Zou, Z. Li, F. Gao, and C. Peng, "A novel deep belief network and extreme learning machine based performance degradation prediction method for proton exchange membrane fuel cell," *IEEE Access*, vol. 8, pp. 176661–176675, 2020.

[25] Y. Wang and X. Li, "Soft measurement for VFA concentration in anaerobic digestion for treating kitchen waste based on improved DBN," *IEEE Access*, vol. 7, pp. 60931–60939, 2019.

[26] Z. Y. Zhao, Y. X. Li, F. Yu, and Y. F. Yi, "Improved deep learning algorithm based on extreme learning machine," *Comput. Eng. Des.*, vol. 4, pp. 1022–1026, 2015.

[27] X. Tan, S. Su, Z. Zuo, X. Guo, and X. Sun, "Intrusion detection of UAVs based on the deep belief network optimized by PSO," *Sensors*, vol. 19, no. 24, p. 5529, Dec. 2019.

[28] W. Tian, D. Wu, Q. Chao, Z. Chen, and Y. Wang, "Application of genetic algorithm in  $M \times N$  reconfigurable antenna array based on RF MEMS switches," *Mod. Phys. Lett. B*, vol. 32, no. 30, 2018, Art. no. 1850365.

[29] C. Puente and J. Romeu, "Perturbation of the Sierpinski antenna to allocate operating bands," *Electron. Lett.*, vol. 32, no. 24, pp. 2186–2188, 1996.

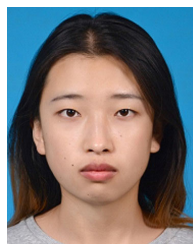
[30] K. J. Vinoy, J. K. Abraham, and V. K. Varadan, "On the relationship between fractal dimension and the performance of multi-resonant dipole antennas using koch curves," *IEEE Trans. Antennas Propag.*, vol. 51, no. 9, pp. 2296–2303, Sep. 2003.

[31] I. Dey, P. S. Rossi, M. M. Butt, and N. Marchetti, "Virtual MIMO wireless sensor networks: Propagation measurements and fusion performance," *IEEE Trans. Antennas Propag.*, vol. 67, no. 8, pp. 5555–5568, May 2019.

[32] L. Aguni, A. El Yassini, S. Chabaa, S. Ibyaich, and A. Zeroual, "Design of a symmetric CPW-fed patch antenna for WLAN/WIMAX applications using ANN," *Wireless Pers. Commun.*, vol. 115, no. 1, pp. 439–456, Nov. 2020.



**JINGCHANG NAN** received the Ph.D. degree in electromagnetic field and microwave technology from Beijing University of Posts and Telecommunications, Beijing, China, in 2007. He was a Senior Visiting Scholar with the University Michigan, in 2012, ICNC-FSDK2013, and CISP-BMEI2014; the Chairman of the CISP-BMEI2015 Organizing Committee; and the Leader of the first-level Discipline of Information and Communication Engineering, Liaoning Technical University. He is currently the Dean, a Professor, and a Doctoral Supervisor with the School of Electronics and Information Engineering, Liaoning Technical University, and a Distinguished Professor of Liaoning Province. His current research interests include RF circuit and systems, electromagnetic field and microwave technology, and communication signal processing and information processing.



**HUAN XIE** received the B.S. degree in electronic science and technology from Liaoning Technical University, Huludao, China, in 2019, where she is currently pursuing the master's degree. Her current research interests include the modeling and design of microwave circuits, and deep neural network modeling technique.



**MINGMING GAO** received the Ph.D. degree, in 2015. She is currently an Associate Professor and a Postgraduate Supervisor with Liaoning Technical University. She has hosted one NSFC project and one Liaoning provincial education department general project. She has published more than 20 academic articles as the first author. Her main research interests include RF circuit and system, RF device behavior modeling, predistortion technology, artificial intelligence, and so on.



**YANG SONG** received the B.S. degree in electronic science and technology from Zhengzhou University, Zhengzhou, China, in 2018, where she is currently pursuing the master's degree. Her current research interests include ultra-wideband antenna and ultra-wideband multiple input multiple output antenna.



**WENDONG YANG** received the B.Sc. degree in applied chemistry and the M.Sc. degree in material chemistry, China, in 2007 and 2010, respectively, and the Ph.D. degree in electronic engineering from Heriot-Watt University, Edinburgh, U.K., in 2019. He is currently a Professor with Liaoning Technical University. Before that, he worked as a Research Assistant with the Technical Institute of Physics and Chemistry, Chinese Academy of Sciences, Beijing. From August 2019 to November 2020, he was a Postdoctoral Researcher with Helmholtz-Zentrum Berlin, Germany. His research interests include flexible printed antennas and flexible electronic materials and devices.

...