Antenna Resonant Frequency Modeling based on AdaBoost Gaussian Process Ensemble

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Abstract **─** The design of electromagnetic components generally relies on simulation of full-wave electromagnetic field software exploiting global optimization methods. The main problem of the method is time consuming. Aiming at solving the problem, this study proposes a regression surrogate model based on AdaBoost Gaussian process (GP) ensemble (AGPE). In this method, the GP is used as the weak model, and the AdaBoost algorithm is introduced as the ensemble framework to integrate the weak models, and the strong learner will eventually be used as a surrogate model. Numerical simulation experiment is used to verify the effectiveness of the model, the mean relative error (MRE) of the three classical benchmark functions decreases, respectively, from 0.0585, 0.0528, 0.0241 to 0.0143, 0.0265, 0.0116, and then the method is used to model the resonance frequency of rectangular microstrip antenna (MSA) and coplanar waveguide butterfly MSA. The MRE of test samples based on the APGE are 0.0069, 0.0008 respectively, and the MRE of a single GP are 0.0191, 0.0023 respectively. The results show that, compared with a single GP regression model, the proposed AGPE method works better. In addition, in the modeling experiment of resonant frequency of rectangular MSA, the results obtained by AGPE are compared with those obtained by using neural network (NN). The results show that the proposed method is more effective.

Index Terms **─** AdaBoost algorithm, Gaussian process ensemble, microstrip antenna, resonant frequency.

I. INTRODUCTION

When studying electromagnetic optimization problems, the electromagnetic simulation software, such as HFSS, is generally used to build the model, and some accurate sample data is obtained by calling the HFSS software for optimization. The general method to optimize microwave structure is using HFSS exploiting global optimization method. However, it will be very time-consuming because HFSS is called for thousands of times for the evaluation of fitness function of the global optimization method. The time may be several days or even several months, and it is insufferable [1]. Based on this problem, many scholars have proposed methods of using surrogate models, such as neural networks (NN) [2,3], support vector machines (SVM) [4,5], linear regression [6,7] and Gaussian process (GP) [8,9], and some have achieved results that meet the standards. However, when using surrogate models, it is still necessary to use the HFSS software to simulate some data. Because it is not easy to obtain a large number of sample data, the accuracy of the established model sometimes cannot meet the requirements. This study proposes an AdaBoost GP ensemble (AGPE) method, using the GP as the weak learning model and the AdaBoost algorithm [10,11] as the ensemble framework.

Submitted On: June 29, 2020
Accepted On: October 20, 2020

https://doi.org/10.47037/2020.ACES.J.351205

Some weak GPs are weighted and integrated to obtain a strong learner. Compared with the single GP, the method proposed in this study can obtain higher accuracy under the premise of the same training samples, while the single GP requires more training samples to achieve the modeling accuracy of the method proposed. Therefore, the proposed method saves the time of using HFSS software to simulate samples.

As a machine learning (ML) algorithm, GP has attracted a lot of attention in recent years [12]. Compared to other ML algorithms such as NN, the GP has two major advantages: 1) The GP requires few parameters to be learned during the training process and is easy to implement; 2) It has a good effect on solving the complex problems of insufficient samples and non-linearity [13]. At present, in the field of electromagnetism, GP has been used as a surrogate model, and some results have been obtained.

With the great leap of modern industrial level, the problems faced are more and more complex. At this time, the concept of ensemble learning [14,15] came into being, and gradually attracted a large number of scholars. In 1990, Schapire used the constructive method to prove the theory that integrating multiple weak learners can get stronger learners, and proved the excellence of integrated learning [16]. In 1996, the Bagging algorithm came out [17]. The algorithm processes training samples through Bootstrap method, and obtains a number of training subsets with the same number but certain similarity. Then, it uses these subsets to train several weak models, and finally integrates several weak models. AdaBoost algorithm was proposed by Freund et al. in 1996 [18], and realized the great leap from theoretical research to practical application of integrated learning. In 2016, Chen et al. proposed an improved Boosting model using residual learning, namely XGBoost [19]. This model and its improved model are very popular in various fields. When dealing with many problems, its learning performance can be compared with that of deep neural network (DNN).

AdaBoost algorithm is proposed on the basis of Boosting, which is one of the three ensemble algorithms. It has been widely concerned in the field of ML [20]. It is applicable to classification and regression problems [21,22], but most of them are currently used to deal with classification problems. In reference [23], the AdaBoost algorithm and decision tree are combined to classify electromagnetic radiation and other related characteristics. In reference [24], the AdaBoost algorithm and NN are combined to classify high-resolution radar. In this study, the AdaBoost algorithm is used to deal with the regression problem, and an algorithm based on the AGPE is proposed. The advantage of the proposed method is illustrated by benchmark functions and resonance frequency of microstrip antennas (MSAs).

II. GAUSSIAN PROCESS

From the mathematical point of view, GP is a kind of functional distribution, which represents a set of random variables subject to joint Gaussian distribution. The GP is uniquely determined by mean function and covariance function [25].

Suppose there is a training sample set, $D=\{(\mathbf{x}_i,\mathbf{y}_i)\}, i=1,\cdots,n,\ \mathbf{x}_i\in R^d, \mathbf{y}_i\in R$. n is the number of samples and d is the dimension of training samples. Then the mean function and covariance function are as follows:

$$m(\mathbf{x})=E\left[f(\mathbf{x})\right], \tag{1}$$

$$k(\mathbf{x},\mathbf{x}')=E\left[\left(f(\mathbf{x})-m(\mathbf{x})\right)\left(f(\mathbf{x}')-m(\mathbf{x}')\right)\right], \tag{2}$$

where $\mathbf{x},\mathbf{x}'\in R^d$ is a random variable, so GP can also be expressed by the following formula:

$$f(\boldsymbol{x})\sim GP(m(\boldsymbol{x}),k(\boldsymbol{x},\boldsymbol{x}')). \tag{3}$$

Assuming that the test sample is $\mathbf{x}*$, the prediction distribution of the GP model is the joint Gaussian distribution formed by the training sample and the test sample:

$$\begin{bmatrix} \boldsymbol{y} \\ f^* \end{bmatrix} \sim N\left\{0,\begin{bmatrix} K(\boldsymbol{x},\boldsymbol{x})+\sigma_n^2\boldsymbol{I} & K(\boldsymbol{x},\boldsymbol{x}^*) \\ K(\boldsymbol{x}^*,\boldsymbol{x}) & K(\boldsymbol{x}^*,\boldsymbol{x}^*) \end{bmatrix}\right\}, \tag{4}$$

where $\mathbf{x},\mathbf{x}*$ is the input of training sample and test sample, $\mathbf{y}, f^*$ is the label of training sample and test sample, and $K(\boldsymbol{x},\boldsymbol{x})$, $K(\boldsymbol{x}^*,\boldsymbol{x})$ is the covariance matrix respectively.

The most important part of GP is the setting of kernel function. Through the mapping of kernel function, the relationship between input and output is established. In general, the setting of kernel function needs to meet Mercer condition [26]. There are many common kernel functions, such as radial basis kernel function, Matern series and so on.

In the training process of GP, only a group of super parameters need to be learned, which is also the only parameter to be determined. The properties of GP are determined by the super parameters that are generally obtained by the maximum likelihood method. The conditional probability of training samples is calculated, and then the logarithmic likelihood function $L(\theta)$ is calculated. The final optimization algorithm is conjugate gradient algorithm [27]. $L(\theta)$ and its partial derivatives are as follows:

$$L(\theta)=-\frac{1}{2}\boldsymbol{y}^T\boldsymbol{C}^{-1}\boldsymbol{y}-\frac{1}{2}\log|\boldsymbol{C}|-\frac{n}{2}\log 2\pi, \tag{5}$$

$$\frac{\partial L(\theta)}{\partial\theta_i}=\frac{1}{2}tr((\boldsymbol{\alpha}\boldsymbol{\alpha}^T-\boldsymbol{C}^{-1})\frac{\partial C}{\partial\theta_i}). \tag{6}$$

After the optimal super parameter is obtained, the test sample can be estimated according to Equations (1) and (2).

III. THE PROPOSED ADABOOST GAUSSIAN PROCESSES ENSEMBLE (AGPE)

AdaBoost is also called adaptive boosting. Its core idea is to generate strong learners by weighted combination of iterative basic learners. This algorithm can effectively avoid over fitting problem [28]. In this study, the algorithm is combined with GP to solve the regression problem. AdaBoost algorithm can be described as follows. First, Bootstrap is used to generate a set of equal number of sub training sets from the original training samples, and each sample is given equal initial weight to train a GP regression model; then the error rate of the model is calculated and the training sample weight is updated according to the error rate; finally, the weight of the model is calculated. By repeating the above process, several models can be obtained, and the output results can be obtained according to the weight ensemble.

Suppose the original sample set is $D=\left\{\left(x_1,y_1\right),\left(x_2,y_2\right),\cdots,\left(x_N,y_N\right)\right\}$, where N is the number of samples. Table 1 is the pseudo code of the proposed AGPE algorithm. The specific steps are as follows:

1) Bootstrap is used to generate a set of sub training sets with the number of N from the original samples D, and each sample is given equal initial weight $W_1=\left(\omega_1,\cdots,\omega_i\right), i=1,\cdots,N$, $\omega_i=1/N$.

2) According to the training subset generated above, the GP is trained and the maximum error on the training set is calculated:
$$E_m=\max\left|y_i-GP_m(x_i)\right|, \tag{7}$$
Calculate the relative error of each sample:
$$e_{mi}=\frac{\left|y_i-GP_m(x_i)\right|}{E}, \tag{8}$$
The error rate of the training set of the model can be obtained:
$$e_m=\sum_{i=1}^{N}\omega_{mi}e_{mi}. \tag{9}$$

3) According to the error rate, the weight coefficient of the model is calculated:
$$\alpha_m=\frac{e_m}{1-e_m}. \tag{10}$$

4) Update sample weight:
$$W_{m+1}=\frac{\omega_{mi}}{Z_m}\alpha_m^{1-e_{mi}}, \tag{11}$$
where Z is a normalization factor:
$$Z_m=\sum_{i=1}^{N}\omega_{mi}\alpha_m^{1-e_{mi}}. \tag{12}$$

5) Repeat the above process K times to get K GP models, and integrate them to get the final model as follows:
$$f(x)=\sum_{m=1}^{K}\left(\ln\frac{1}{\alpha_m}\right)GP_m(x). \tag{13}$$

Table 1: Pseudo code of the proposed AGPE algorithm

Input: Training set $D=\left\{\left(x_1,y_1\right),\left(x_2,y_2\right),\cdots,\left(x_N,y_N\right)\right\}$;
Iteration times T.

Initialize: $W_1(i)=1/N$, where $i=1,2,\cdots,N$.

Do for: $t=1,2,\cdots,T$

1. Use Bootstrap to generate a subset of the training sample D_t from D.
2. Use the training subset D_t to train the weak learner GP_t .
3. Calculate the error rate of the basic learner on the training set e_t :
$$e_t=\sum_{i=1}^{N}W_t(i)\varepsilon_t,$$
$$\varepsilon_t=\frac{\left|y_i-GP_t(x_i)\right|}{\max\left|y_i-GP_t(x_i)\right|},$$
If $e_t>0.5$, then go to step 1 to continue the cycle;
End if
4. Let $\alpha_t=\ln\frac{e_t}{1-e_t}$;
5. Update the weight of training samples W_t ;
$$W_{t+1}(i)=\frac{W_t(i)}{Z_t}\alpha_t^{1-\varepsilon_t},$$
Where Z_t is the normalization factor;

End for

Output: Final regression:
$$f(x)=\sum_{t=1}^{N}\left(\ln\frac{1}{\alpha_t}\right)GP_t(x).$$

IV. CASES STUDY

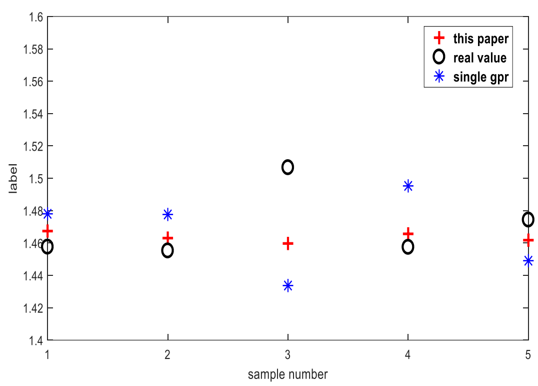
A. Benchmark functions

In this part, three classical benchmark functions are selected to verify the superiority of the proposed AGPE algorithm. The specific information of the test functions is shown in Table 2. At the same time, in order to show the superiority of the proposed method, it is compared with a single GP regression model, and mean relative error (MRE) is selected as the evaluation index, which is defined by:
$$MRE=\frac{1}{n}\sum_{i=1}^{n}\frac{\left|f(x_i)-y(x_i)\right|}{y(x_i)}. \tag{14}$$

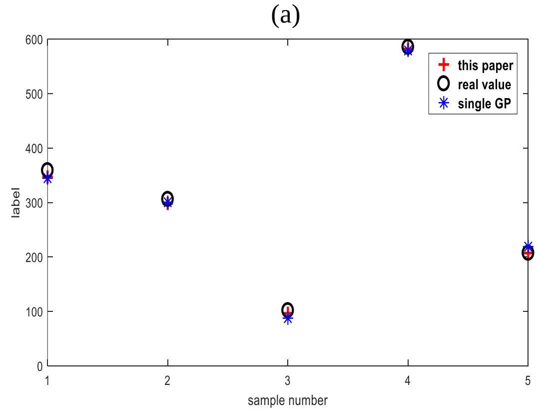
Table 2: Benchmark functions

Function	Function Expression	Dim.	Search Space
Schaffer	$f(x)=0.5+\frac{\left(\sin\sqrt{x_1^2+x_2^2}-0.5\right)}{\left(1+0.001\left(x_1^2+x_2^2\right)\right)^2}$	2	-100～100
Rastrigin	$f(x)=\sum_{i=1}^{n}\left(x_i^2-10\cos\left(2\pi x_i^2\right)+10\right)$	3	-20～20
Schwefel	$f(x)=418.9829n+\sum_{i=1}^{n}\left(x_i\sin(\sqrt{\lvert x_i\rvert})\right)$	3	-500～500

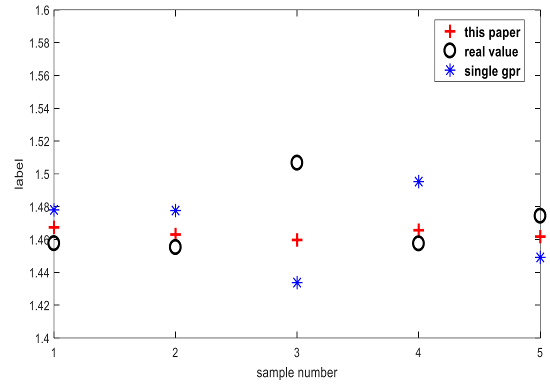
In this case, the number of samples $NP=35$, in which 5 groups are randomly selected as test samples and the rest as training samples. Table 3 shows the MRE comparison between the proposed model and a single model on the test set, and Fig. 1 shows the comparison of the prediction results of test samples between the proposed method and a single model. The abscissa in the figure represents the number of test samples, and the ordinate represents the value corresponding to the test samples. According to the results in Table 3 and Fig. 1, the MRE of the three benchmark functions is 0.0585, 0.0528 and 0.0241 respectively by single GP, whereas the MRE is 0.0143, 0.0265 and 0.0116 respectively by the proposed method in this paper. Therefore, the modeling effect of the method proposed in this paper is better than that of the single GP model.



(a)



(b)



(c)

Fig. 1. Prediction results comparison of test samples: (a) for Schaffer function, (b) for Rastrigin function, and (c) for Schwefel function.

Table 3: MRE comparison of the benchmark functions

Methods	Schaffer	Rastrigin	Schwefel
Single GP	0.0585	0.0528	0.0241
This paper	0.0143	0.0265	0.0116

B. Resonant frequency modeling of rectangular MSA

Antenna plays an irreplaceable role in the communication system. MSA has the advantages of small size, light weight and easy fabrication, and has been widely used in aerospace, medical, mechanical and other fields [29]. The MSA can be set to different shapes as required. In this paper, the resonant frequency of rectangular MSA is used for modeling, and its structure is shown in Fig. 2.

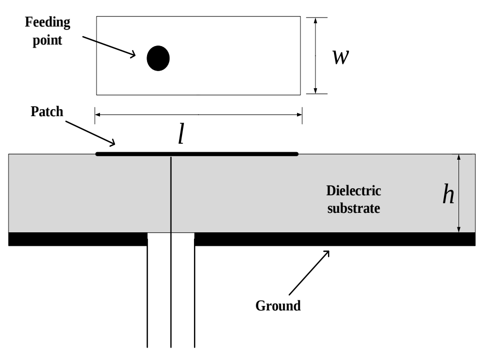


Fig. 2. The rectangular MSA.

In this modeling, the width *w*, length *l*, height *h* and dielectric constant ε_r of the MSA are as input, and the resonance frequency f_{11} (MHz) is as output. We select 33 groups of data from Reference [30] and list them in Table 4 to model according to the proposed AGPE method, in which those with tag* are test sample. The prediction results of this paper are compared with other literature and single GP.

Table 4: Resonant frequency of the rectangular MSA in TM_{10} mode

w (cm)	l (cm)	h (cm)	ε_r	f_{ME}	f_{EDBD}	f_{DBD}	f_{BP}	f_{AGPE}	f_{GP}
0.850	1.290	0.017	2.22	7740*	7935.5	7890.1	7858.6	7965	8032.8
0.790	1.185	0.017	2.22	8450	8328.2	8226.0	8233.1	8450	8450
2.000	2.500	0.079	2.22	3970	4046.4	4023.0	4075.4	3970	3970
1.063	1.183	0.079	2.25	7730	7590.1	7567.3	7616.8	7730	7730
0.910	1.000	0.127	10.2	4600	4604.8	4573.9	4592.4	4600	4600
1.720	1.860	0.157	2.33	5060*	4934.2	4914.0	4930.3	5041	5156.3
1.810	1.960	0.157	2.33	4805	4699.2	4684.8	4703.3	4805	4805
1.270	1.350	0.163	2.55	6560	6528.6	6502.8	6516.5	6560	6560
1.500	1.621	0.163	2.55	5600*	5503.2	5473.3	5449.0	5601	5535.3
1.337	1.412	0.200	2.55	6200	6176.6	6142.6	6147.2	6200	6200
1.120	1.200	0.242	2.55	7050	7099.6	7064.3	7132.9	7050	7050
1.403	1.485	0.252	2.55	5800	5805.6	5768.8	5765.7	5800	5800
1.530	1.630	0.300	2.50	5270	5287.7	5260.3	5254.0	5270	5270
0.905	1.018	0.300	2.50	7990	7975.5	7881.8	8002.2	7990	7990
1.170	1.280	0.300	2.50	6570*	6674.8	6632.8	6682.7	6558	6600.5
1.375	1.580	0.476	2.55	5100	5311.8	5293.2	5291.4	5100	5100
0.776	1.080	0.330	2.55	8000	7911.1	7841.6	7942.5	8000	8000
0.790	1.255	0.400	2.55	7134	7183.2	7162.1	7215.9	7134	7134
0.987	1.450	0.450	2.55	6070*	6173.0	6155.1	6170.2	6074	6040.7
1.000	1.520	0.476	2.55	5820	5931.0	5918.0	5924.5	5820	5820
0.814	1.440	0.476	2.55	6380	6424.0	6417.5	6430.7	6380	6380
0.790	1.620	0.550	2.55	5990	5866.1	5873.9	5870.5	5990	5990
1.200	1.970	0.626	2.55	4660	4699.0	4728.0	4718.9	4660	4660
0.783	2.300	0.854	2.55	4600*	4459.1	4517.1	4519.2	4644	4847.4
1.256	2.756	0.952	2.55	3580	3659.8	3655.7	3644.6	3580	3580
0.974	2.620	0.952	2.55	3980	3952.9	3982.6	3975.9	3980	3980
1.020	2.640	0.952	2.55	3900	3905.4	3930.0	3922.2	3900	3900
0.883	2.676	1.000	2.55	3980	3938.8	3970.7	3965.3	3980	3980
0.777	2.835	1.100	2.55	3900	3825.5	3851.1	3845.9	3900	3900
0.920	3.130	1.200	2.55	3470*	3481.4	3466.2	3458.4	3465	3478.1
1.030	3.380	1.281	2.55	3200	3230.3	3184.7	3178.0	3200	3200
1.265	3.500	1.281	2.55	2980	3036.1	2965.6	2961.2	2980	2980
1.080	3.400	1.281	2.55	3150	3191.2	3140.4	3134.0	3150	3150
Absolute error sum of all data					2329	2427	2372	**310**	770
MRE of test samples					0.0192	0.0162	0.0174	**0.0069**	0.0191

In Table 4, the training data of rectangular MSA are given in columns 1~4, the measured value in column 5, and the NN results given by Guney et al. [30] are listed in columns 6~8, and f_{EDBD}, f_{DBD}, f_{BP}, respectively, represent the predicted resonance frequency of the NN model using the EDBD (extended delta bar delta), DBD (delta bar delta) and BP (back propagation) algorithm. Columns 9 and 10 respectively show the results obtained by using the proposed method in this paper and the single GP model. At the same time, the absolute error sum of each method is given in the penultimate row of Table 4, and the MRE of test samples according to the proposed method and other models is given in the penultimate row. It can be seen from Table 4 that the total absolute error calculated by the proposed method in this paper is 310MHz, which is superior to the calculation results of other documents and single GP, and the MRE of test sample is smaller than that of other models, which shows the excellence and effectiveness of the proposed algorithm in this paper.

C. Resonant frequency modeling of coplanar waveguide (CPW) butterfly MSA.

In order to verify the effectiveness of the proposed method further, the resonance frequency of coplanar waveguide (CPW) butterfly MSA (shown in Fig. 3) is modeled. Through HFSS simulation software, training data are obtained. Selecting h, W, L are as input data, and resonance frequency f_{11} (MHz) is as output, where h represents the thickness of the dielectric substrate, L, W respectively represents the length of the butterfly antenna and the length corresponding to the opening Angle. 30 groups of data are selected for modeling, in which 25 groups are as training data and the other 5 groups are as testing data. Finally, the result computed by the proposed AGPE algorithm is compared with that of single GP, shown in Fig. 4 and Table 5. We can see from Fig. 4 and Table 5 that the MRE of the AGPE model and single GP model are 0.0008 and 0.0023 respectively, and the prediction value of the AGPE model is closer to the real value than that of single GP, which means the accuracy and generalization performance of the AGPE model is better than that of single GP.

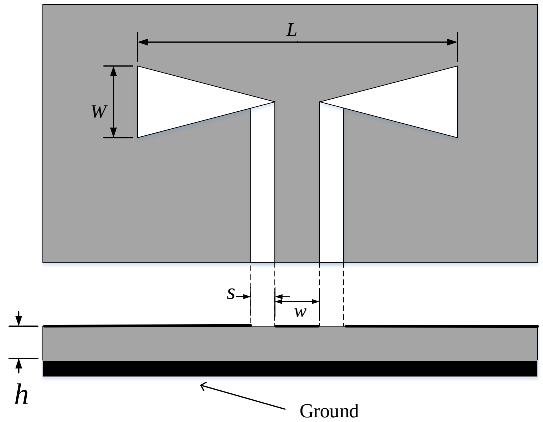


Fig. 3. The CPW butterfly MSA.

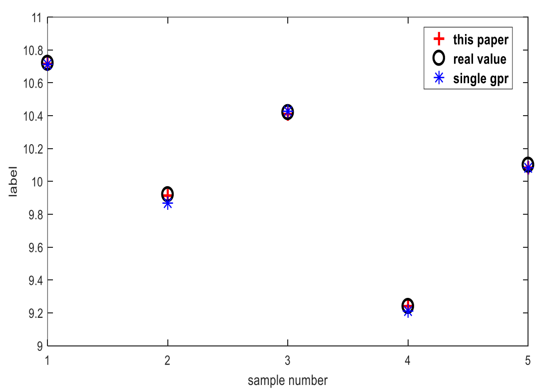


Fig. 4. Prediction results comparison of test samples for the CPW butterfly MSA

Table 5: Simulation results of the CPW butterfly MSA

Methods	MRE
Single GP	0.0023
This paper	0.0008

V. CONCLUSION

This study proposes an algorithm named AdaBoost Gaussian process ensemble (AGPE). The core of this algorithm is to use Gaussian process as weak learner and the AdaBoost algorithm as ensemble framework. Firstly, we obtain a group of weighted weak learners, and then integrate them to get the final strong learner. Through modeling of the benchmark functions and the resonant frequencies of rectangular microstrip antenna and coplanar waveguide butterfly microstrip antenna, it can be seen that the proposed AGPE method has higher accuracy than that of single GP. At the same time, compared with the neural network method in other literature, the proposed AGPE method also shows some advantages. The proposed method in the study is also easily be used in other microwave components modeling in the field of electromagnetics.

ACKNOWLEDGMENT

This work is supported by the National Natural Science Foundation of China (NSFC) under No. 61771225 and Jiangsu Province Qinglan project.

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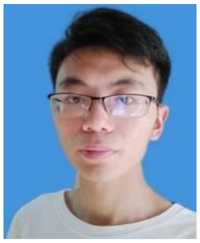

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