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ОПТИМИЗАЦИЯ ПАРАМЕТРОВ МЕТАМАТЕРИАЛА-ФАЗОМАНИПУЛЯТОРА С ПРИМЕНЕНИЕМ НЕЙРОСЕТЕВОГО МОДЕЛИРОВАНИЯ И ГЕНЕТИЧЕСКОГО АЛГОРИТМА

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OPTIMIZATION OF METAMATERIAL PHASE MANIPULATOR PARAMETERS USING NEURAL NETWORK MODELING AND GENETIC ALGORITHM

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Аннотация. Для прогнозирования характеристик метаматериала-фазоманипулятора проведена оптимизация соответствующих параметров такого устройства с использованием искусственной нейронной сети и генетического алгоритма. Показано, что относительная погрешность определения значений исследуемых параметров не превысила 1% по сравнению со значениями, рассчитанными методом конечных элементов.

Ключевые слова: *метаматериал*, *фазоманипулятор*, *планарная спираль*, *искусственные нейронные сети*, *генетический алгоритм.*

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Abstract. To predict the characteristics of the metamaterial-phase-manipulator, the optimization of the relevant parameters of such a device was carried out using an artificial neural network and a genetic algorithm. It is shown that the relative error in determining the values of the investigated parameters did not exceed 1% compared to the values calculated by the finite element method.

Keywords: *metamaterial*, *phase manipulator*, *planar spiral*, *artificial neural networks*, *genetic algorithms.*

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Introduction

Metamaterials and metasurfaces have significant scientific interest for many research groups around the world. These artificial structures possess unique properties not observed in natural materials: a negative refraction index, low diffraction limit of an object image, complete absorption in a specific frequency range, etc. [1]–[4].

Currently, artificial neural networks and genetic algorithms are successfully used in various fields of science and technology. Artificial neural networks provide the ability to find complex nonlinear dependencies in the studied functions of many arguments, which manifest when modeling the interaction of electromagnetic waves with metamaterials. Genetic algorithms are a specific case of evolutionary methods based on collective learning within a population and imitating natural selection. Genetic algorithms provide the search for the best solutions by inheriting and enhancing the useful properties of many objects during the simulation of their evolution [5]–[11].

In this work, artificial neural networks and genetic algorithms are applied to predict and optimize the parameters of a metamaterial for the possibility of phase manipulation of electromagnetic waves when interacting with a metasurface based on planar resonators.

1 Modeling

The project of a metamaterial phase manipulator consisting of 25-paired planar spiral resonators located on a dielectric layer is built via Ansys HFSS software (Figure 1.1, *a*). The resonators are copper strips and cylinders connecting both sides of the structure. Each resonator also contains a varicap.

The metamaterial modeling was based on double-sided FR4 fiberglass with a core thickness of 1.5 mm and copper layers with a thickness of 35 microns. As a screen behind the metamaterial, a single-sided FR4 fiberglass surface was used with the same core and copper layer thickness.

The wavefront emitted by the metasurface with given radiation pattern diagram parameters (Figure 1.1, *b*) is formed due to the presence of a difference in wave paths or phase shift of the wave. This is achieved by changing the capacitance of the varicaps on neighboring resonators. By setting the capacitance value C of the varicaps in the first row (since in each row C is the same), and then in the next row according to the required phase difference, it is possible to control the tilt of the main lobe of the metamaterial's radiation pattern diagram in the XOZ plane.

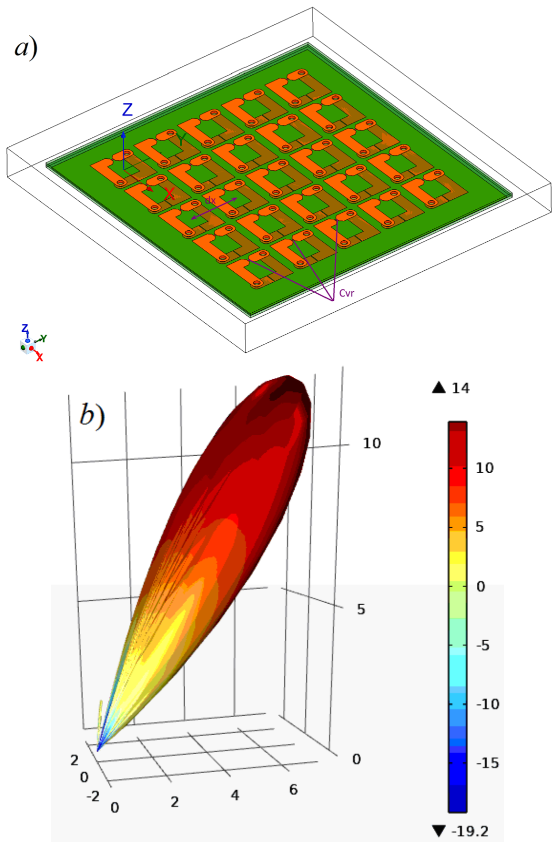


Figure 1.1 – The project of the metamaterial consisting of 25-paired planar spiral resonators located on the dielectric layer (*a*); an example of a radiation pattern diagram formed by the metasurface (*b*). Here, dx is the distance between the centers of resonators in the metasurface, Cvr is the varicap with the specified capacitance.

To form the training and testing data arrays for artificial neural networks, the radiation pattern calculations were performed using the finite element method in Ansys HFSS.

The input parameters are adjusted in such a way that the metamaterial has a radiation pattern diagram with the minimum lobe width, which allows obtaining concentrated space radiation of maximum power. During the research, it was found that the most effective parameters for solving this problem are the inter-element distance (spatial period of the metasurface dx) and the capacitance of the varicaps.

The geometric parameters of the planar spiral resonators were pre-determined by analytical methods for calculating the polarizations of any particle of arbitrary shape, the linear dimensions of which are small compared to the wavelength, as described in the work [12].

2 Solving optimization problem

During the numerical experiment, a sample formed in the DesignXplorer module of the Ansys Software was used.

According to the experiment plan, the calculations were performed for two input parameters: P1 is varicap capacitance Cvr, P2 is inter-element distance dx. At the same time, the following output parameters were determined: the electric field intensity at the maximum of the radiation pattern diagram E and the lobe width of the radiation at half the power of the radiation dTheta. Thus, the research object model was response functions linking the output parameters (E, dTheta) with the factors (dx, Cvr) (Table 2.1).

Figure 2.1 shows the dependencies of E and dTheta on the input parameters, and Figure 2.2 shows their response surfaces.

Table 2.1 – Parameters of planar spiral resonators

Input parameters	Value of input parameters
P2 (dx, mm)	28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40
P1 (Cvr, pF)	0.1–0.5

The calculations were performed for 533 combinations of input parameters (Figure 2.1), 513 of which used for training artificial networks and 20 for testing (Table 2.2).

Artificial neural networks were formed using the TensorFlow machine-learning library. The ReLu activation function, Adam optimizer, and MSE loss function were used in creating the networks. The neural network underwent training for a total of 700 epochs. As a result, 25 artificial neural networks were created with the number of neurons in the two hidden layers ranging from 10 to 50 with an interval of 10.

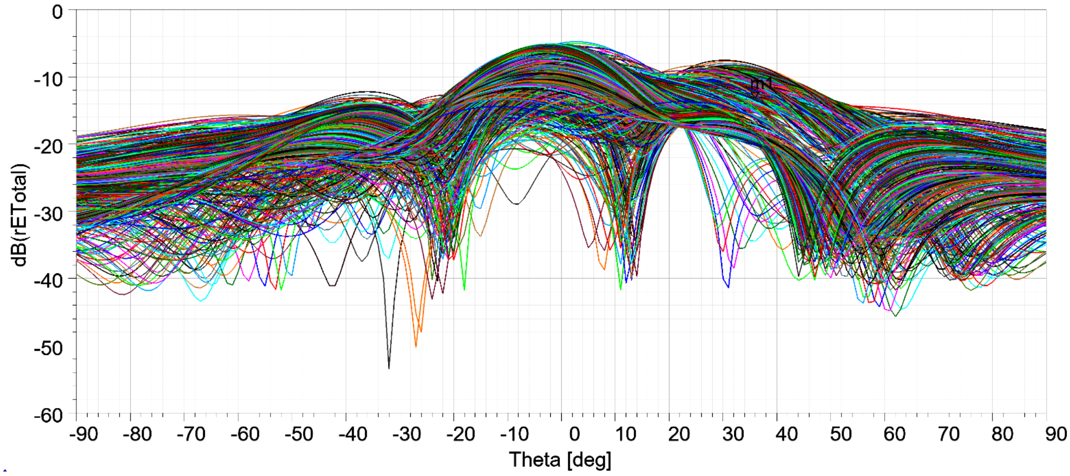
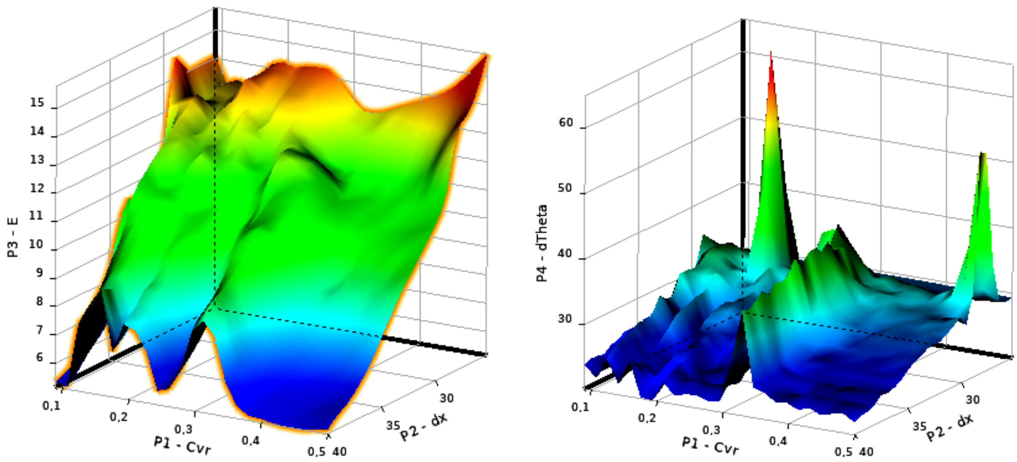


Figure 2.1 – Dependence of electric field intensity on the angle of rotation of the radiation pattern diagram



a) *b*)

Figure 2.2 – Response surfaces of E (*a*) and dTheta (*b*)

Table 2.2 –Test dataset

N	Cvr, pF	dx, mm	E, dB	dTheta, deg
1	0.24	30	11.31	29
2	0.24	32	10.36	28
3	0.21	38	8.31	25
4	0.12	31	12.97	34
5	0.44	29	10.80	31
6	0.45	36	6.87	25
7	0.22	33	11.78	29
8	0.39	30	10.34	31
9	0.38	28	11.19	32
10	0.32	34	11.12	42
11	0.48	34	8.26	27
12	0.17	36	9.28	23
13	0.37	33	9.20	29
14	0.14	33	11.51	25
15	0.49	38	5.94	23
16	0.43	33	8.84	28
17	0.41	29	10.71	31
18	0.11	31	12.14	30
19	0.12	35	11.02	31
20	0.19	28	13.35	63

The following criteria were used to evaluate the obtained models: root mean squared error (*RMSE*), mean absolute error (*MAE*) and the coefficient of determination R^2:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(d_i - y_i\right)^2},$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|d_i - y_i\right|, \quad R^2 = 1 - \frac{\sum_{i=1}^{n}\left(d_i - y_i\right)^2}{\sum_{i=1}^{n}\left(d_i - \bar{d}\right)^2},$$

where d_i represents the values, calculated using finite element analysis; y_i denotes the values, calculated using neural network predictions.

Figure 2.3 shows the heat maps illustrating the distribution of validation errors in determining the output parameters. The vertical and horizontal axes show the number of neurons in the first and second hidden layers of artificial neural networks, respectively. The intensity of the color-coding indicates the magnitude of the error: the error increases as the color transitions from light to dark.

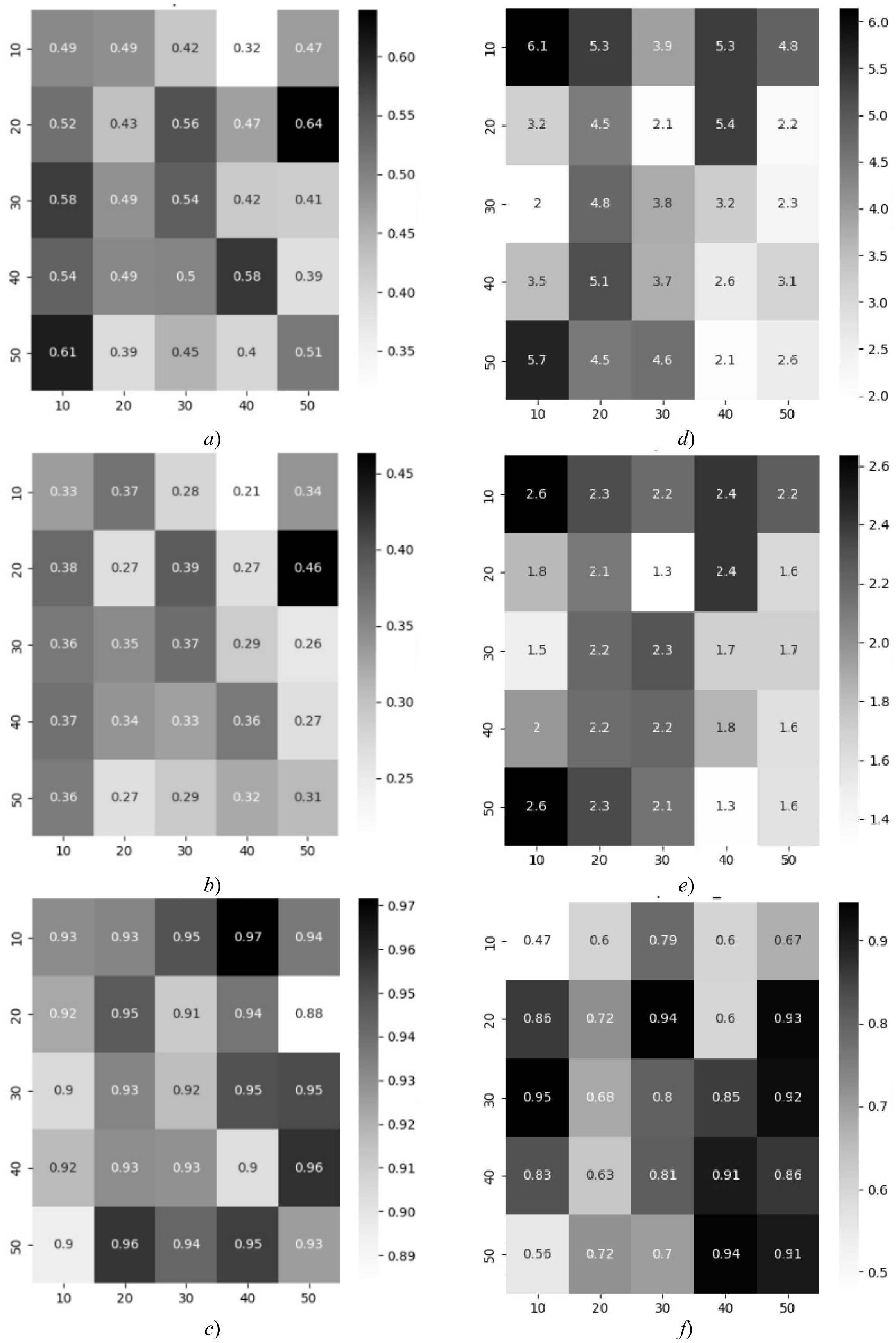


Figure 2.3 – Heat maps of distribution *RMSE* (*a*), *MAE* (*b*), R^2 (*c*) (darker color there means higher determination) for E and heat maps of distribution *RMSE* (*d*), MAE (*e*), R^2 (*f*) (darker color there means higher determination) for dTheta

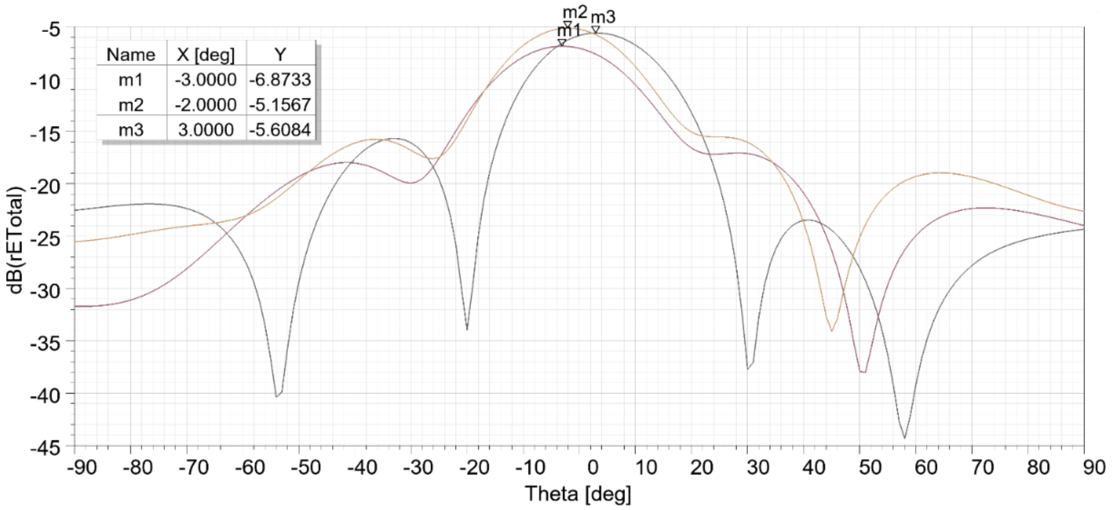


Figure 2.4 – Candidate points calculated via finite element analysis

The neural network with the architecture [2-10-40-2] demonstrated superior performance in determining the values of E, whereas the network with the architecture [2-50-40-2] achieved the highest accuracy in determining the values of dTheta. Here, the numbers 2 in square brackets indicate the fact that the analysis is performed using two input and two output parameters. Table 2.2 presents the evaluation results of the corresponding neural network models.

Table 2.2 – Results of neural network model evaluation

Criteria	E	dTheta,
RMSE	0.3 dB	2.1 deg
MAE	0.2 dB	1.3 deg
R^2	0.9715	0.9398

The optimization problem was to find the minimum module of the intensity E, expressed in decibels, and the minimum dTheta. The lobe width of the radiation at half power was calculated from the maximum intensity of the obtained directional diagram by subtracting 4 dB.

Table 2.3 presents the values of the candidate points found through the genetic algorithm. Figure 2.4 shows the actual values of these points, calculated via the finite element analysis. The minus signs on the Y-axis indicate that the values taken in decibels; however, we considered the modules of these values and it is easy to notice that the values predicted by the neural network closely match the analytical ones.

Table 2.3 – Values of candidate points

Point	1	2	3
P2 – dx, mm	40	37.6949	36.0617
P1 – Cvr, pF	0.4551	0.1013	0.4957
P3 – E, dB	5.1408	5.6246	6.8716
P4 – dTheta, deg	21.8735	22.7504	23.8187

Conclusion

The obtained results allow us to conclude that neural network models are sufficiently effective in predicting the parameters of metamaterials, which in turn provides the possibility of optimizing the corresponding parameters using genetic algorithms. At the same time, the relative error in determining the values of the studied parameters did not exceed 1% compared to the values calculated using the finite element method.

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