

# MULTIPARAMETER HYBRID NEURAL NETWORK METAMODEL OF EDDY CURRENT PROBES WITH VOLUMETRIC STRUCTURE OF EXCITATION SYSTEM

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**Abstract:** A multiparameter metamodel of the eddy current probe with the volumetric excitation structure is constructed. As variable parameters of the metamodel, the spatial coordinates of the testing zone, the radii of the excitation coils and the height of their location above the testing object were used. Due to the use of hybrid construction of multiple neural networks using decomposition of the search space, an acceptable metamodel's error of the eddy current probe with volumetric excitation structure is obtained.

**Keywords:** EDDY CURRENT PROBE, UNIFORM SENSITIVITY, VOLUMETRIC EXCITATION STRUCTURE, EDDY CURRENTS DENSITY, NEURAL NETWORKS, HYBRID RBF-METAMODEL

## 1. Introduction

Some difficulties associated with the non-uniform sensitivity of the probe in the testing zone are characteristic for the defectometry problems solution by the eddy current method. The non-uniform sensitivity is due to the exponential eddy currents density distribution (ECDD) in the testing object (TO) and is inherent in any type of excitation coils, so their using in this case is not effective. In defectometry the best sensitivity characteristic in the testing zone is considered to be uniform, the so-called P-shaped. In this case, the effect of the dependence of the probe sensitivity to the location of the defect in the testing zone is reduced. Thus, there is a need to create eddy current probes (ECP) with uniform sensitivity, and, consequently, the uniform ECDD in the TO zone. One of the ways to solve this kind of problem is the optimal surrogate synthesis of the excitation system (ES) of ECP. Using parametric non-linear synthesis, a sectioned excitation coil system is created and takes into account the shape, electrophysical parameters of the TO and a priori given uniform sensitivity characteristic.

In [1] the problem of the linear synthesis of ECP with a given structure of the excitation field in the TO zone is considered. In addition, since the linear values of the ECDD were obtained with the help of linear synthesis, the practical implementation of such ECP's is complicated. The cases, when the given field structure is obtained with non-linear parameters of the probe are not considered in these work.

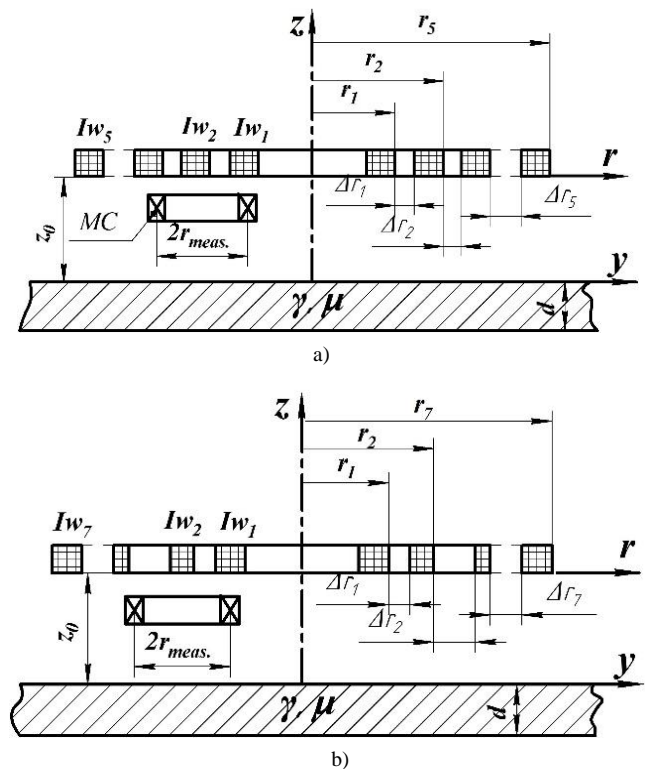
The non-linear synthesis problem was solved in [2]. The problem solution for the optimal placement of the section coils and their geometric dimensions provided the fixed value of the excitation current density in them is obtained. The structural-parametric synthesis method of the source of the electromagnetic field [3] allows us to solve the problem of choosing the structure of the ES ECP. However, the presence of a conductive medium and the speed effect, i.e. at motionless ECP relatively TO is not taken into account.

## 2. Background and means to solve the problem

A number of works by the authors of [4–6] are devoted to solving the problems of the non-linear, in the general case, synthesis of non-coaxial circular EDP's with a planar ES structure. A characteristic feature of a planar ES structure is the presence of  $M$  coils of radii  $r_k$  ( $k = 1...M$ ) with their uniform  $\Delta r = const$  or non-uniform  $\Delta r = var$  arrangement, which are at the same height  $z_0$  above the TO [7] and switched on counter or consensually "across the field" (Fig. 1). For such task the synthesis parameters are three variables  $J=f(x, y, r)$ : spatial coordinates  $x, y$  of the testing zone and the radii of the excitation coil sections  $r$ .

Moreover, the obtained ES of planar design with a uniform or un-uniform arrangement of coils provides a value of the reduced error in the uniform of the ECDD in the testing zone from 9 to

11 %, which is not an entirely acceptable result, and leaves the desire to further improve the structure of the ES [4-8].



**Fig. 1** Variants of the arrangement of the coil sections of the surface ECP with a planar ES structure: a) uniform  $\Delta r = const$ ; b) un-uniform  $\Delta r = var$ ; MC - measuring coil

## 3. The solution to the problem

As a result, there is a need to study probes with a volumetric structure of ES, both of a homogeneous and heterogeneous structure (Fig. 2).

The arrangement of coils of surface ECP's of a volumetric ES can be either uniform when  $\Delta r = const, z_1 = z_k = const$ , or non-uniform  $\Delta r = const, z_1 \neq z_k$  (Fig. 3).

In contrast to the planar structure of the ES, the number of parameters of the synthesis problem increases, i.e. the height of the coils above TO  $z_0$  is added  $J=f(x, y, r, z_0)$ . As in the simpler case of the planar design of the probe, one cannot do without the ECP metamodel  $\hat{J}=f(x, y, r, z_0)$ , which significantly reduces the calculation time and it becomes possible to solve the synthesis problem.

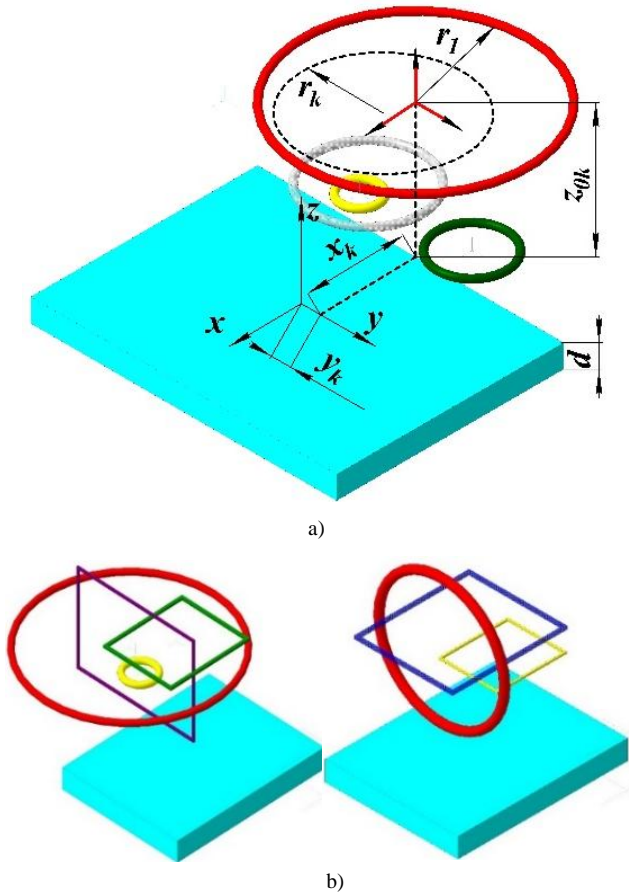


Fig. 2 Volumetric structures of ES ECP: a) homogeneous; b) heterogeneous

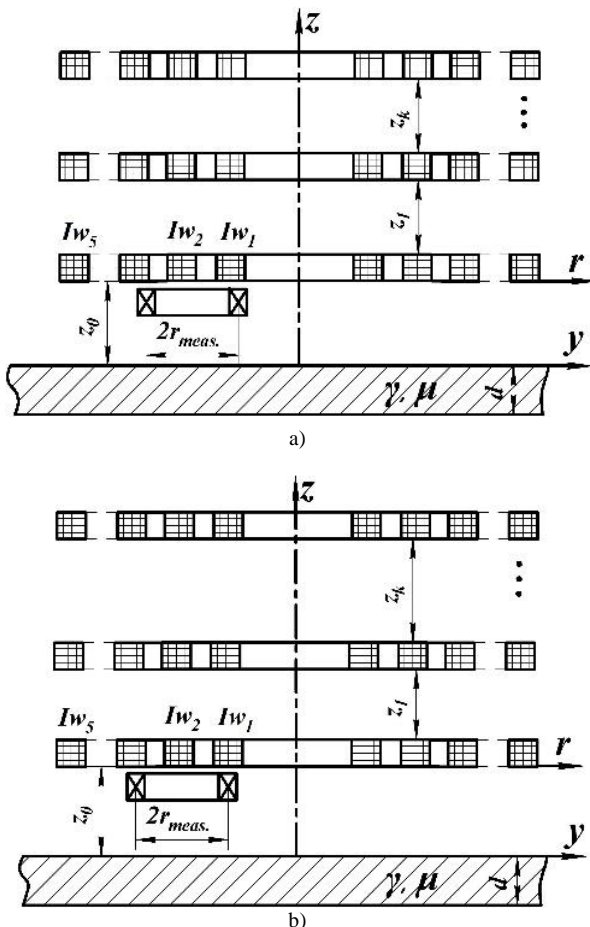


Fig. 3 Arrangement of sections of coils of surface ECP's of a volumetric homogeneous structure ES: a) uniform  $\Delta r = \text{const}$ ,  $z_l = z_k = \text{const}$ ; b) non-uniform  $\Delta r = \text{const}$ ,  $z_l \neq z_k$

The aim of the work is constructing a multiparameter hybrid RBF-metamodel of eddy current probes with volumetric homogeneous excitation structure.

On the basis of a mathematical model of a moving surface ECP, which was obtained analytically by solving the direct problem of electrodynamics in the form of Maxwell's differential equations [6], a neural network metamodel that takes into account the change in four parameters simultaneously  $\hat{J}=f(x, y, r, z_0)$  was constructed.

The metamodel for the moving structure of the ES ECP in the form of ampere-coils located at different heights above the TO (Fig. 3) with the following initial data: TO thickness  $d = 10$  mm; excitation current frequency  $f = 5$  kHz; electrophysical parameters of the material TO  $\sigma = 3,745 \cdot 10^7$  Sm/m,  $\mu_r = 1$ , the speed of the probe relative to TO  $\vec{v} = (40, 0, 0)$  m/s was constructed. Variable model parameters are: spatial coordinates of the testing zone  $x = -45 \dots 45$  mm;  $y = 0 \dots 35$  mm; the radii of the coils ES  $r = 2 \dots 15$  mm; their height above TO  $z_0 = 2 \dots 5$  mm.

Next, the construction of a metamodel of a moving surface ECP in accordance with the algorithm proposed in [6, 7] is performed. It is advisable to approximate the multidimensional response surface using the heuristic method based on artificial neural networks. This method has some significant advantages in comparison with well-known methods [9]. An RBF-neural network with a Gaussian activation function as a multidimensional approximator was used. However, unlike the simpler case of an optimization problem with three variables, a number of difficulties arise in this case. Firstly, the response surface has a complex topography, which imposes certain limitations associated with the need to use a big data array in the procedure of training a neural network. Secondly, there is a big range of ECDD values in the range of radius changes. This is especially true for the region beyond the ES, which entails an ununiform distribution of the ECDD values at the points of the experiment plan (Fig. 4), which necessitates the decomposition of the search space. All this greatly complicates the constructing of a multiparameter metamodel and it is almost impossible to implement it on the simplest, so-called single RBF-neural networks.

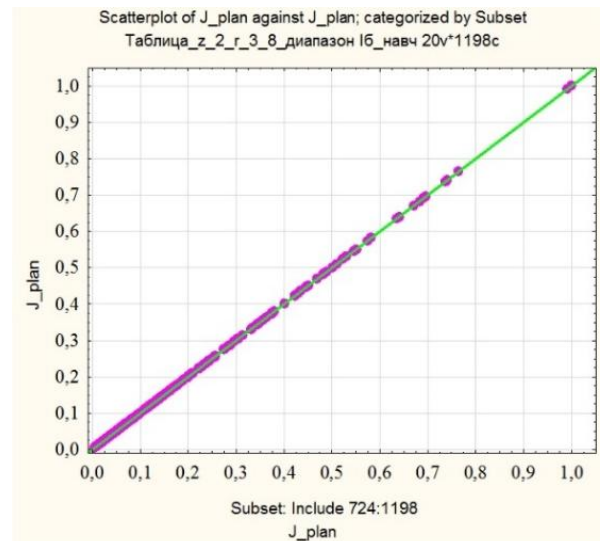


Fig. 4 Normalized ECDD values for the subregion  $I_z - III_z$  of the testing zone beyond the ES

The decomposition along the height of the probe and along the radius manages to partially level a number of these difficulties. The decomposition along the height of the probe above the TO is performed into three subregions:  $I_z (2 \leq z \leq 3 \text{ mm})$ ,  $II_z (3 < z \leq 4 \text{ mm})$ ,  $III_z (4 < z \leq 5 \text{ mm})$ . The decomposition along the radius of the coil turns is performed into six subregions:  $I_r (2 \leq r \leq 3 \text{ mm})$ ,  $II_r (3 < r \leq 5 \text{ mm})$ ,  $III_r (5 < r \leq 8 \text{ mm})$ ,  $IV_r (8 < r \leq 10 \text{ mm})$ ,  $V_r (10 \leq r \leq 12 \text{ mm})$ ,  $VI_r (12 < r \leq 15 \text{ mm})$ . Additionally, if necessary, the radius of the search space is further divided into two subregions - directly under the turns of the coil

sections and beyond them. In order to construct the metamodel as accurately as possible, the number of points of the experiment plan at which the eddy current density is calculated is set different for the area under the turns of the coil sections and beyond them. Thus, it is possible to simplify the architecture of a single RBF-neural network and achieve a certain balance between the accuracy of the construction of the metamodel and the number of points in the experiment plan of the  $N_{training}$ . In this case, not classical methods of experiment planning are used, but computer methods of homogeneous filling with search points of hyperspace, namely, points of the Sobol's  $LP_\tau$ -sequence  $\zeta_1, \zeta_2, \dots, \zeta_{52}$  [10]. So, for example, for the subregion  $I_{z_0}$  and all subregions along the radius  $I_r - VI_r$ , where such  $LP_\tau$ -sequences as  $\zeta_1, \zeta_2, \zeta_3, \zeta_4$  in the region immediately under the coil sections, and  $\zeta_1, \zeta_3, \zeta_4, \zeta_2$  realized beyond it. Those, we have the arrangement of points of the  $LP_\tau$ -sequence in a multifactorial space, respectively, in the  $x$  and  $y$  coordinates of the testing zone, in the radius  $r$  of the excitation coils and the height of their location above the TO  $z_0$  (Fig. 5). The number of points for each subregion is set individually depending on the size of the excitation coil and, accordingly, the size of the region under it. Accounting the symmetry of the ECDD concerning to the coordinate axes also influences the choice of the number of points, i.e. for a moving probe they are specified for  $I$  and  $II$  quadrants. For example, for  $I_z - II_r$  the size of the testing area directly under the coil is  $x = -17..17$  mm;  $y = 0..13.5$  mm. For the most accurate description of the behavior of the response surface, the number of points for the training sample was chosen  $N_{training} = 1749$  (Fig. 6), while beyond the region -  $N_{training} = 1198$ .

3D Scatterplot of r against x and y; categorized by Subset and Subset  
Таблица\_z\_2\_r\_3\_8\_диапазон I6\_навч 21v\*1223c

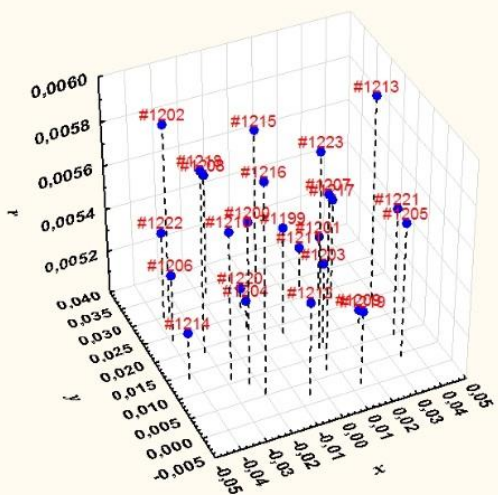


Fig. 5 Arrangement of points of the  $LP_\tau$ -sequence  $\zeta_1, \zeta_3, \zeta_4, \zeta_2$  in three-dimensional factor space for  $r = 5..6$  mm at a fixed height  $z = 2$  mm

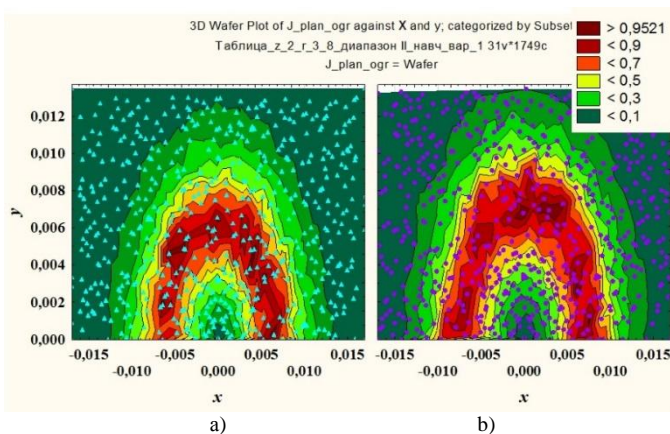


Fig. 6 A training sample, presented in the form of lines of ECDD, with points of the  $LP_\tau$ -sequence for the  $I_z - III_r$  subregion: a)  $r = 6 - 7$  mm; b)  $r = 7 - 8$  mm

Acceptable accuracy of the metamodel was obtained using hybrid neural network construction. This implies the construction of several cascades of neural networks with subsequent additional application at each committees cascade (Fig. 7) [6]. As a function of activation of neurons in a hidden layer of an RBF-network the Gauss function is used. Then the output of the neural network is formed by a linear combination of the outputs of the neurons of the hidden layer and is described by the formula:

$$\hat{J}(x, y, r, z) = \sum_{i=1}^m w_i \cdot \exp \left( -\frac{(x-c_{xi})^2 + (y-c_{yi})^2 + (r-c_{ri})^2 + (z-c_{zi})^2}{a_i^2} \right),$$

where  $m$  is the number of neurons in the hidden layer;  $w_i$  is the weighting coefficient of the output neuron with the  $i$ -th neuron of the hidden layer;  $c_{xi}, c_{yi}, c_{ri}, c_{zi}$  are coordinates of the center of the  $i$ -th neuron;  $a_i$  - the width of the  $i$ -th neuron.

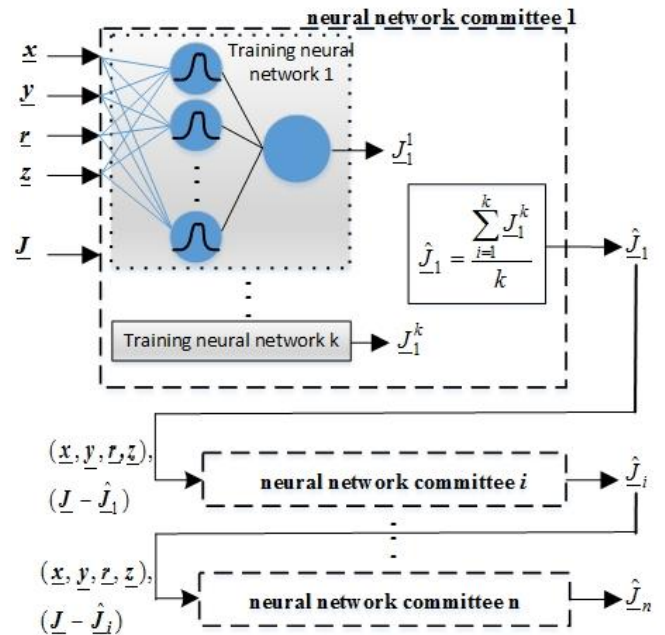


Fig. 7 Hybrid construction of a neural network metamodel

For the network's committee only networks with the productivity of the training, testing, and controlling samples of more than 90 % are used. The number of cascades is determined by the obtained value of the mean absolute percentage error MAPE, %. The best models were selected according to a combination of objective statistical indicators [10] and a subjective assessment of dispersion diagrams and histograms of residues.

Table 1 shows the obtained values of MAPE, % at the stage of training and reconstitution of neural networks for several decomposition subregions.

#### 4. Results and discussion

Verification of the metamodel was carried out by checking the correctness of reconstitution of the response surface in all subregions on the sample, which has a bigger number of points than during training, i.e.  $N_{reconstitution} > N_{training}$ . To illustrate this, Fig. 8 shows the dispersion diagrams of the values of the multidimensional approximation function for one of the  $I_z - III_r$  subregions at the stages of training the neural network and its reconstitution.

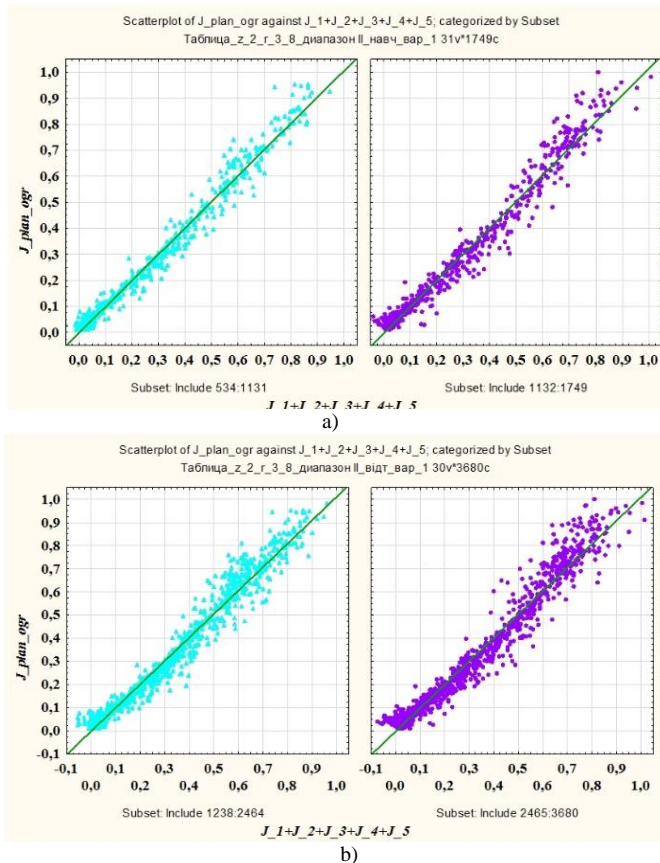


Fig. 7 Diagram of the dispersion of the values of the multi-dimensional approximation function for the subregions  $I_2-III_r$ : a) the stage of training the neural network; b) the stage of reconstitution

The adequacy of the obtained metamodel was evaluated according to the statistical F-criterion based on the following indicators: the sum squares of the regression and residues ones; the average square of the regression and residuals at a significance level of 5 % [10]. The information content of the constructed metamodel is controlled by the coefficient of determination.

Table 1: Values of MAPE,% of the obtained multi-parameter hybrid neural network metamodel of ECP for several decomposition subregions.

Decomposition subregions	$N_{training}/N_{reconstitution}$	MAPE,%	
		stage training	stage reconstitution
$I_2-III_r$ (beyond coil)	1198/2186	16,72	21,17
$I_2-III_r$ (under coil)	1749/3680	19,09	21,31
$II_2-I_r$ (under coil)	900/1250	4,35	6,22

Thus, due to the use of hybrid construction of multiple neural networks using decomposition of the search space, an acceptable error in the metamodel of the volumetric structure of the ES EDP is obtained.

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