DEVELOPMENT OF ALGORITHMS FOR COMPLEX NUMERICAL OPTIMIZATION OF OBJECTS WITH MODULAR STRUCTURE

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Abstract: The authors considered numerical methods of structural optimization of modular electrodynamic objects and selected some effective procedures that allow creating objects with given properties. A block diagram of the combined algorithm containing the calculation and optimization part is presented. To calculate the characteristics of the scattering of electromagnetic waves, the method of integral equations is used. This method was also used to determine the radar cross section (RCS). In the article, the dimensions of an object with a complex structure are obtained, which give the minimum mean RCS values. The presented combined algorithm can be used in CAD systems for the design of complex electrodynamic objects.

Key words: optimization of the particle swarm, electromagnetic scattering, modular structure.

1. INTRODUCTION

The study of numerical methods for optimizing the structure of electrodynamic modular objects and the selection of appropriate effective methods are closely related to the process of modeling optimization and structural synthesis [1]. These methods are used in electrodynamic CAD. The model for optimizing an electrodynamic object is based on integrated algorithms for multi variant optimization, most of which relies on a randomized scheme for finding promising solutions in many alternative variables [2, 3].

In this paper, optimization is used to determine the average value of the scattering parameters (EPR) of electrodynamic objects, which are calculated on the basis of the integral equations method.

A lot of structure components are associated with the corresponding alternative variables by representing discrete numbers corresponding to these elements in binary terms.

We introduce a vector of random values of alternative variables $\tilde{x} = (\tilde{x}_1, \dots, \tilde{x}_j, \dots, \tilde{x}_J)$, where the alternative variable $\tilde{x}_j$:

$$\tilde{x}_j = \begin{cases} 1, \; \textit{if the subset of the modular object structures } s \in S, \textit{obtained as} \\ \textit{a result of the dichotomous division is promising} \\ \textit{in terms of requirements } F_i^{'}, (i = \overline{1,I}) \\ 0, \; \textit{otherwise} \end{cases} \qquad (1)$$

and it has the following distribution $p(\tilde{x}_J = 1) = px_j$, $p(\tilde{x}_J = 0) = qx_j = 1 - px_j$.

The first variant (algorithm 1) of the construction of the combined algorithm is related to the need to accelerate the convergence of distributions of alternative variables in the neighborhood of either the probability value 1 or the probability value 0 [4, 5].

The effect on the convergence on one side of the connection to the tuning of probabilities at each step of the particle swarm method is researched on [6-7] and on the one hand, the influence of the initial distributions and internal parameters of the algorithm.

The second variant (algorithm 2) of the construction of the combined algorithm is aimed at ensuring the reduction of many promising solutions of the basic procedure of multi-alternative optimization. Such a reduction is achieved by replacing the insufficiently successful variants with more successful ones and then reducing their number on the basis of connecting the schemes of crossing and multiplying genetic algorithms.

Finally, the third variant (algorithm 3) of the construction of the combined algorithm is based on a combination of a randomized search scheme for multi-alternative optimization and a dialog procedure for multi-alternative optimization with a choice of the kind and parameters of convolution of local criteria in the integral optimized function according to expert estimates [8, 9] [10, 11].

2. METHOD FOR OPTIMIZING A MODULAR OBJECT

To solve optimization problems, the authors used the iterative variational procedure of multi-alternative optimization, based on the determination at each k^{th} (k = 1, 2 ...) of the search step for the variation of the optimized function F with respect to the variable x_j:

$$\Delta_j^k = F(\tilde{x}^k / x_j = 0) - F(\tilde{x}^k / x_j = 1), \qquad (2)$$

where $\tilde{x}^k = (\tilde{x}_1, \ldots, \tilde{x}_\pi, \ldots, \tilde{x}_J)$, $\pi = \overline{1,J}$, $\pi \neq j$ - vector of random realizations of alternative variables having a distribution

$$p_{x_\pi} = p(\tilde{x}_\pi = 1), \; q_{x_\pi} = p(\tilde{x}_\pi = 0), \; p_{x_\pi} + q_{x_\pi} = 1,$$

p(.)- Random event probability designation.

At the initial stage of optimization using the system of computational experiment, the variations are determined on the basis of the results of the full-scale experiment, and with the accumulation of information sufficient for constructing the simulation model in accordance with this model in which the values of the variables $x_t^{'}$, $y_t^{'}$, $z_t^{'}$, $t = \overline{1,T}$, where T is the total number of coordinates of the object under study, which are calculated from the values corresponding to the values of alternative variables x_j, $j = \overline{1, J}$.

The random value of the alternative variable is defined as follows:

$$\tilde{x}_\pi = \begin{cases} 1, if \;\; p_{x_\pi} > \tilde{\xi} \\ 0, otherwise \end{cases},$$

where $\tilde{\xi}$ - a discrete random variable having a uniform distribution on the interval [0, 1] [1].

In the first step k = 1, the value $p^1_{x_\pi}$ is given by the researcher. The most frequent option is $p^1_{x_\pi} = 0{,}5$, but other options may be researched on.

You can define several such implementations for the j-th variable. Then they are used when predicting the direction of the change in the probability value p_{x_j} at the k-th integration with a random step $\tilde{B}_J$ that takes the value 1 and 0 in accordance with the distribution:

$$p_{B_{j_n}} = p(\tilde{B}_J = 1), \; q_{B_{j_n}} = p(\tilde{B}_J = 0) = 1 - p_{B_{j_n}}. \qquad (3)$$

Taking into account the multiple realization (2), a proposal is made to control the distribution (3), based on the value of the variation and distribution of the random step $\tilde{c}_J$ of the next level:

$$p_{c_{j_n}} = p(\tilde{c}_J = 1), \; q_{c_{j_n}} = p(\tilde{c}_J = 0) = 1 - p_{c_{j_n}}.$$

In order to make full use of the hidden information [1], the value of the probability $p_{B_{j_n}}$ must be increased for the purpose of a more noticeable change p_{x_j} for the case when the signs of the first $\Delta_{1j}F$ and second $\Delta_{2j}F$ realizations of the variation F coincide and decrease otherwise. This rule corresponds to the following scheme of determination $p_{B_{j_n}}$ on the new (k + l)[th] iteration:

$$p^{k+1}_{B_{j_n}} = p^k_{B_{j_n}} + p^{k+1}_{Bj}\chi(\Delta^k_{1j}F\Delta^k_{2j}F) - p^k_{Bj}\chi(-\Delta^k_{1j}F\Delta^k_{2j}F), \qquad (4)$$

where the value $p^{k+1}_{B_{j_n}})$ is given depending on the expected effect of the predicted term in (4) by the value p_{Bm},

$$\chi(a) = \begin{cases} 1, if \;\; a > 0, \\ 0, if \;\; a < 0. \end{cases}$$

After adjusting the step size, we correct the distribution of the variable x_j based on the law of prognostic evaluation (2). We note that the probability p_{x_j} increases for the case when there is a positive value of the first realization (2) and otherwise decreases:

$$p_{x_j}^{k+1} = p_{x_j}^{k} + p_{x_j}^{k+1}(q_{xj}^{k}\chi(\Delta_{1j}F) - p_{x_j}^{k}\chi(-\Delta_{1j}F)). \quad (5)$$

To further improve the efficiency of the use of hidden information within the framework of the algorithmic scheme (5), it is important not only to sort out the coordinates x_j, but to control the choice of coordinates using the third realization for a random variable [12, 13]. At the same time, if one assumes that in carrying out a sequential search of probability, the implementation of the attraction to the search for coordinates is the same, i.e. in the first step:

$$p_J^1 = \frac{1}{J}\ \forall j = \overline{1,J},$$

then during the search process the probability p_j must be increased when there is a coincidence of the signs of the realizations of the quantity (2) and reduce otherwise. Such a change should be made using some random step $\tilde{d}$ having a distribution:

$$p_d = p(d=1),\ q_d = p(d=0) = 1 - p_d.$$

It is necessary to maintain the normalization condition

$$\sum_{j=1}^{J} p_{x_j}^{k} = 1.$$

In this case, carrying out changes in one of the probability values p_j leads to the fact that all the others $p_\pi = (\pi = \overline{1,J}; \pi \neq j)$ change.

The algorithmic scheme is presented in the following form:

$$p_j^{k+1} = p_j^{k} + p_d^{k+1}(q_{xj}^{k}\chi(\Delta_{1j}F\Delta_{3j}F) - p_{x_j}^{k}\chi(-\Delta_{1j}F\Delta_{3j}F)). \quad (6)$$

To maintain the normalization conditions for the remaining probabilities, it is necessary to carry out the recalculation in this way [13, 14]:

$$p_j^{k+1} = \frac{q_j^{k+1}A_\pi}{\sum\limits_{\pi=1\ \pi\neq j}^{M} A_\pi},\ A_\pi = \frac{p_\pi^{k}}{p_j^{k+1}}(\pi \neq j).$$

The multilevel variational procedure considered requires calculating a sufficiently large number of steps K until a situation is attained when most of the probability values p_{2m}. enter the intervals of variation (0, δ), (1-δ, 1), 0 <δ << 1, δ - small number. As a research component, it is suggested that within this procedure it is not necessary to carry out a movement with one set of probabilities p_{x_j}, $j = \overline{1,J}$ and for n ($n = \overline{1,N}$) sets $p_{x_{jn}}$, using the combined procedure with the particle swarm method [15, 16].

In this case we have $n = \overline{1,N_r}$ particles with coordinates p_{j_n}, $n = \overline{1,N_r}$, $j = \overline{1,J}$ which change at each k-th step according to the scheme [17, 18]:

$$p_{x_{jn}}^{k+1} = p_{x_{jn}}^{k} + \upsilon_{x_{jn}}^{k+1}, \quad (7)$$

where υ_{j_n} - coordinates of the velocity vector of the n-th particle

$$\upsilon_{j_n}^{k+1} = p_{B_j}^{k+1}(q_{x_{j_n}}^k \chi(\Delta_{1j_n} F) - p_{x_{j_n}}^k \chi(-\Delta_{1j_n} F)).$$

In order to synchronize procedure (7) of the swarm particle method [19, 20] and the variational procedure of multi-alternative optimization (6) at each step, we will update the rate of change of coordinates of not all particles at once, but one particle, whose movement to the extremum of the optimized function is the most promising [21, 22].

Controlling particle selection to update the rate of change of coordinates is proposed to be carried out using a randomized scheme. To this note, a random discrete quantity $\tilde{n}$ is introduced, of accepted value $\tilde{n} = \overline{1, N_r}$ with a probability of pn. In the first step

$$p_n^1 = \frac{1}{N_r} \forall n = \overline{1, N_r}\ .$$

Then, changing the values p_n^k on condition $\sum_{n=1}^{N_r} p_n^{\nu_k} = 1$ is carried out as follows.

The value of the random variable $\tilde{n}$ is determined. Let $\tilde{n} = \nu$. Then the rate of change of coordinates on the (k+1)-th step is calculated [23]:

$$\upsilon_j^{k+1} = \begin{cases} \upsilon_{j_n}^k \ \forall n = \overline{1, N_r}, n \neq \nu, \\ p_{x_{j_n}}^{k+1}(q_{x_{j_n}}^k \chi(\Delta_{1j_n} F) - p_{x_{j_n}}^k \chi(-\Delta_{1j_n} F)), n = \nu. \end{cases},$$

and the value of probabilities p_n

$$p_n^1 = \begin{cases} \dfrac{p_n^k}{1+\varepsilon^{k+1}} \forall n = \overline{1, N_r}, n \neq \nu, \\ \dfrac{p_n^k + \varepsilon^{k+1}}{1+\varepsilon^{k+1}}, n = \nu \end{cases}$$

where $\varepsilon^{k+1} = \varepsilon^k \, exp(\mu(sign(\Delta_\nu^{k-1} \nabla_\nu^k)))$, $\mu > 0$ - parameter that is specified during the search.

In this case, the quantity $\varepsilon > 0$ determines the degree of record-breaking motion of the ν -th particle in the direction to the extremum of the optimized function F:

$$\nabla_\nu^k = R_\nu^k - R_S^k,$$

where $R_\nu^k = max(F(\tilde{x}_\nu^k / x_{j\nu} = 0), F(\tilde{x}_\nu^k / x_{j\nu} = 1))$ – a record for the function F for a particle ν in determining the variation with the j -th alternative variable,

$R_s^k = max_{s=\overline{1,S}}(F(\tilde{x}_s^k / x_{js} = 0), F(\tilde{x}_s^k / x_{js} = 1))$ – record for the function F for $s = \overline{1, S}$ neighboring particles in determining the variation (2) with respect to the *j*-th alternative variable, s -the number of the neighboring particle in accordance with the concept of particle neighborhood, which is defined in the particle swarm method.

As a neighborhood topology, a cluster topology is adopted, since it provides a better change in the information propagation speed within the swarm of particles. In this case, the graph consists of N_r = 16 particles, which are distributed as a clique on 4 particles in four nodes (figure 1).

In this case, if on two adjacent steps the record R_ν ν -th particle exceeds the record R_s neighboring particles, then the quantity $\varepsilon^{k+1} = \varepsilon^k \, exp(\mu)$ increases, leading to an increase p_ν^{k+1} and reduction of all others p_n^{k+1}.

This means that the frequency of choice of the particle ν - the leader in the random search is increased, and the movement to the extremum of the optimized function becomes effective.

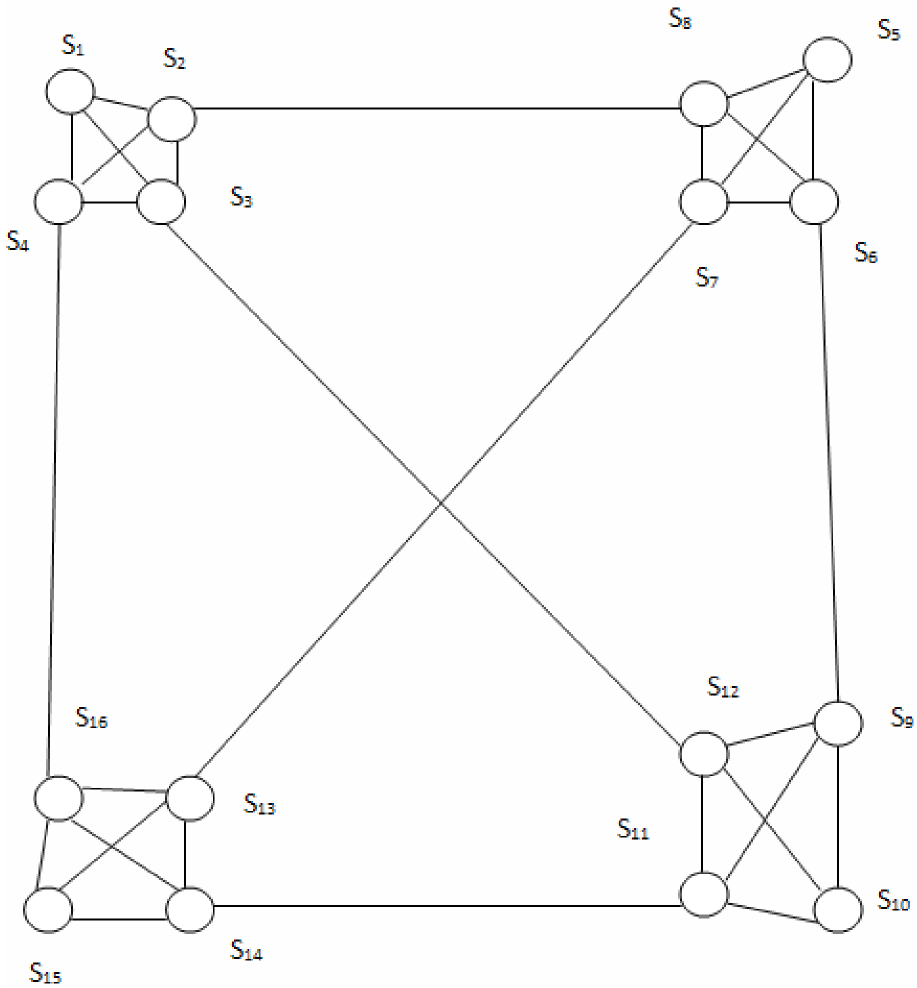

Fig. 1. Cluster topology of the particle neighborhood

In another situation, when at two neighboring steps there is no stable record of the ν-th particle with respect to the neighboring particle, the signs ∇_{ν}^{k-1} и ∇_{ν}^{k} are different, and the value $\varepsilon^{k+1} = \varepsilon^{k} / exp(\mu)$ decreases, which does not allow to significantly change the frequency of the choice of the particle v, as it has not manifested itself as a stable particle - the leader.

Thus, a multi-level search control scheme in a randomized algorithm of multi-alternative optimization is supplemented by another level in the framework of a controlled swarm of particles.

It is possible to research to what extent the integration of different algorithms contributes to a further increase in the efficiency of automatic procedures for the structural synthesis of an object, depending on the initial values of the probabilities $p_{x_j}^1$, $p_{B_j}^1$, $p_{C_j}^1$, $j = \overline{1,J}$, p_d^1 parameters values δ, μ >0, number of particles N_r and topology of the neighborhood, different from that considered in figure 1 (other number of nodes in the case of cluster topology, the number of particles in the clique, the node other types of topologies: clique, ring, two-dimensional torus, dynamic topologies). Particles S_1, S_5, S_{10}, S_{15} have three neighboring particles, the remaining have four.

The structural scheme of realization of the algorithm combined with the swarm method (algorithm 1) of multi-alternative optimization, oriented to carrying out the computational experiment, is shown in fig. 2.

3. THE METHOD OF INTEGRAL EQUATIONS

This method is used to determine the dispersion properties of each of the components of a modular object and further calculate the dispersed field from the entire object.

The integral equation of the first order for the unknown electric current density in the case of E-polarization [24] has the form:

$$\frac{\omega\mu}{4}\int_{\alpha}^{\beta} j(t) H_0^2 [kL_0(\tau,t)] \sqrt{\xi'^2(t) + \eta'^2(t)} = E_z^0(\tau) \quad , \alpha \le \tau \le \beta \qquad (8)$$

here $L_0(\tau,t) = \sqrt{[\xi(\tau) - \xi(t)]^2 + [\eta(\tau) - \eta(t)]^2}$ – distance from the point of observation to the point of integration, $E_z^0(\tau)$ – The longitudinal component of the strength of the primary electric field at a point on the contour.

The contour of the object is given in parametric form: $x = \xi(t)$, $y = \eta(t)$, $\alpha \le t \le \beta$, и $\xi'(t), \eta'(t)$ – first derivatives of the corresponding functions, $k = 2 \cdot \pi / \lambda$, λ – length of incident electromagnetic wave.

When solving equation (7) using the method of moments, we applied discretization and obtained a system of linear algebraic equations, from which we determined the longitudinal electric currents with the density

$$\vec{j} = \vec{z} \cdot j(t), \; \alpha \le t \le \beta . \qquad (9)$$

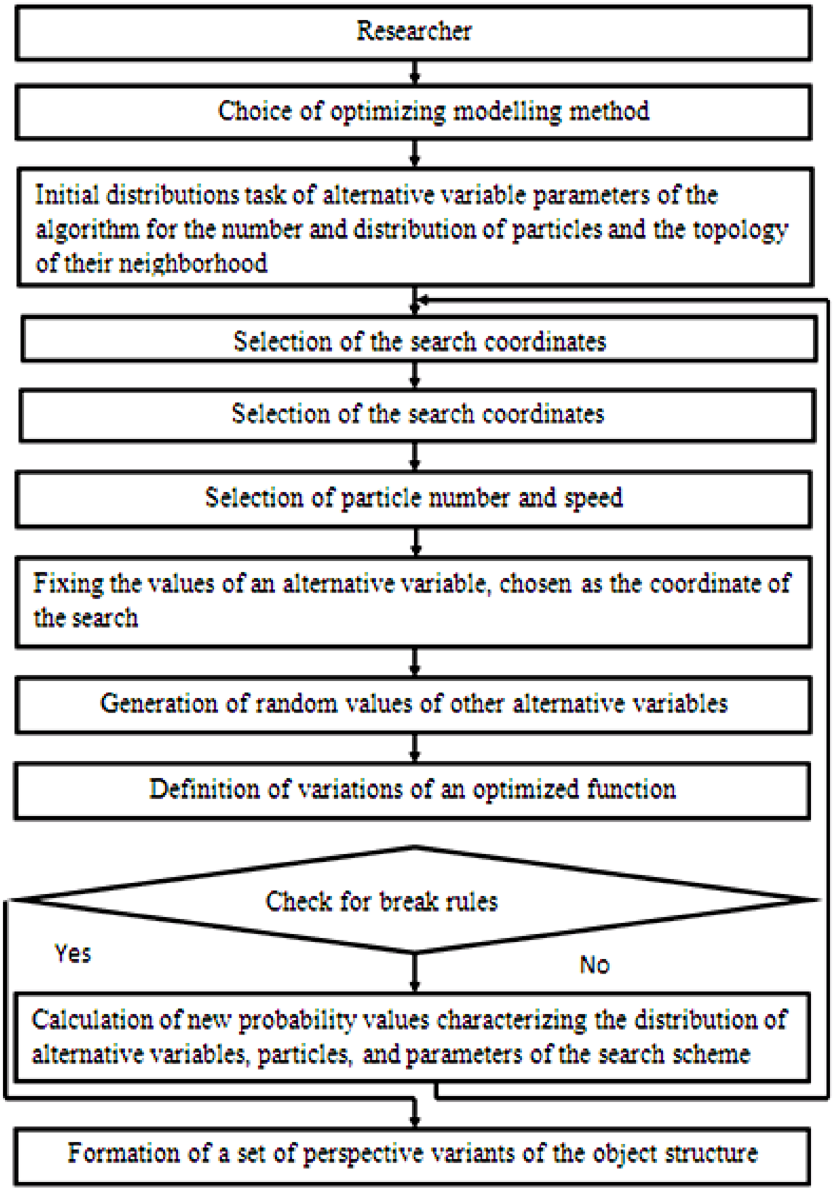

Fig. 2. Block diagram of the combined algorithm for the method of multi-alternative optimization and optimization based on a swarm of particles

The two-dimensional EPR of an object can be calculated on the basis of expression

$$\sigma(\varphi) = (60 \cdot \pi)^2 \cdot k \cdot |D(\varphi)|^2, \qquad (10)$$

where $D(\varphi) = \int_{\alpha}^{\beta} j(t) \cdot \sqrt{\xi'^2(t) + \eta'^2(t)} \cdot exp(i \cdot k \cdot d(t,\varphi))dt,$

$$d(t,\varphi) = \xi(t) \cdot cos(\varphi) + \eta(t) \cdot sin(\varphi).$$

The average EPR can be calculated on the basis of expression

$$\overline{\sigma} = \sum_{i=0}^{N} \frac{\sigma(\theta_i)}{N+1}, \qquad (11)$$

here $\sigma(\theta_i)$ - the value of the EPR at the observation angle θ_i.

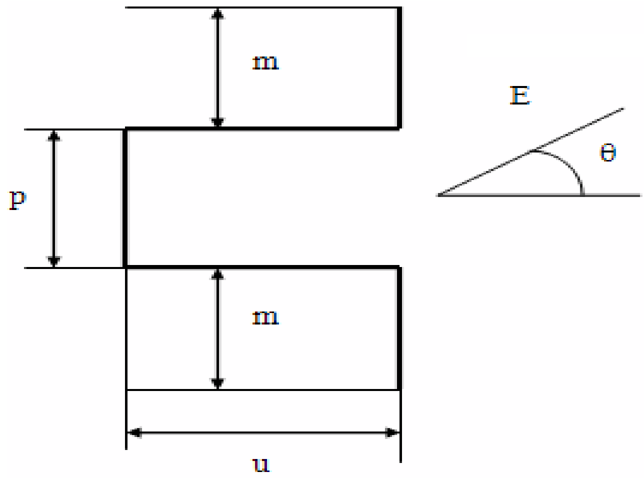

Fig. 3. The object on which the electromagnetic wave dispersion was researched on

4. RESULTS

In the diffraction approach, the object was viewed as a body having a complex shape (figure 3), on which an electromagnetic wave is dispersed. Practical use for the body of a complex form of the method of integral equations and other numerical methods is difficult, but for bodies whose dimensions lie in the resonance range, it is possible to obtain acceptable results.

The advantage of the method of integral equations is the possibility of obtaining data without a natural experiment, since it is replaced by a "computer" experiment. Data can be used not only for analyzing the solution of a direct problem, but also for studying the possibilities of solving inverse problems, that is, determining the shape of the body or the surface of reflection of the properties of objects and constructing algorithms for predicting radar characteristics in the wavelength range.

Integral equations for a single body can be generalized to a system of bodies. Under the domain of integration and the area of change of the observation point in the tiaky case, one should understand the surface of not one but all bodies.

In modeling, we tried to ensure that the average RCS of a given sector of angles had a minimum value, applying the algorithm shown in figure. 2, we get the size of the object under consideration. For viewing angles $0°\leq\theta\leq30°$ we determined the size of the analyzed object: m=2.7λ, u=3.4λ, p=4.6λ for the minimum value of the average EPR.

5. CONCLUSIONS

In this work, the problem of optimization of the dispersed electromagnetic waves on the basis of a multicriteria alternative method of optimization of a swarm of particles was considered. The authors also formed an integrated algorithm and demonstrated the results of its functioning. The results of the work can be used in CAD systems when designing objects with the required values of dispersed electromagnetic fields.

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