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SYSTEM ANALYSIS OF PROPERTIES OF COATINGS AND INDICATORS OF THE PROCESS OF PLASMA AND ELECTROLYTIC OXIDATION'S QUALITY

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Abstract: The article is devoted to solution of the problem of systematization of the parameters for the model that associate the properties of the obtained coatings with the qualitative properties of coatings on the basis of the method of plasma-electrolytic oxidation (PEO) of valve metals. Nowadays for the synthesis of the required parameters of technological processing regimes (electrical regimes, concentrations of the components of the electrolyte) in the process of coatings' forming various measured parameters of the coating are used. At the same time, the final task is not to obtain the parameters of the coating, but its qualitative properties, which are required for diverse terms of use. This leads to necessity of transition from the model "parameters of coating - processing parameters" to the model "indicators of quality - processing parameters".

Keywords: model of interconnection; plasma and electrolytic oxidation; quality criteria; parameters of technological regimes.

I. INTRODUCTION

One of the common ways in which multifunctional coatings are formed on the surface of parts made of valve metals in electrolyte solutions using electric current is the process of plasma electrolytic oxidation [1]. The question of choosing the parameters of the technological mode for obtaining coatings with desired properties that meet the requirements for further use is an important task. It is solved in the overwhelming majority of cases for each specific vector of input and output parameters [2-4]. Moreover, the vector of input parameters is a set of combinations of possible controlled parameters of the process equipment, the base material of the work piece, as well as the composition and concentration of electrolyte components. Output parameters can be considered the coating parameters, which include the thickness of the transition, working and technological layers, micro porosity (closed, open, through), micro hardness at various depths of the coating, adhesion of the coating material to the base of the parts, morphological and component composition of the layers and its distribution in coating thickness, etc. The purpose of the coating formation process is to obtain the quality properties and functionality that the item acquires as a result of processing. The quality indicators include: thermal conductivity, crack resistance, corrosion resistance, wear resistance, strength, breakdown voltage, fluid retention, resistance to cyclic temperature differences, etc. However, in the models proposed by various authors, the required processing modes and parameters of these modes are built on the basis of the coating parameters, and not on the basis of the quality properties that the processed part acquires [5, 6].

II. METHODOLOGY & RESULTS

The study describe the connection of the coating parameters with its qualitative features, we apply a systematic approach. As a system, we consider a set of elements (vectors of input and output parameters), relations (functional dependencies between variables) and the environment. The system environment is the technology of obtaining the coating, the materials to be coated and the equipment used. The goal is to obtain a rational set of coating parameters based on the vector of specified quality indicators. This will provide the possibility of transition from the vector of functional requirements to the vector of coating parameters.

In view of the difficulty of obtaining analytical dependencies between qualitative features and parameters of coating, mathematical empirical models are used to describe their connection. The models are created on the basis of experimental data obtained as a result of studying the influence of the properties of coatings on their qualitative features.

The connection map of various parameters and functional dependencies that provide a description of the interaction between these elements during the PEO process is shown in Figure 1.

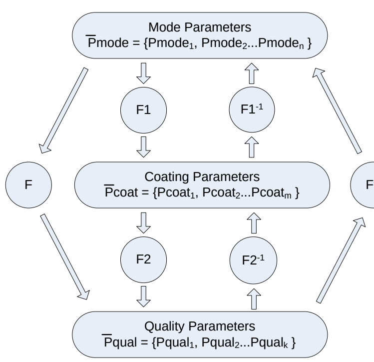

Fig. 1: Diagram of parameters and functional dependencies of PEO

The task that is posed when creating a model is to obtain such a function F2-1, which would allow determining the necessary values of vector $\overline{Pcoat}$ based on a given vector $\overline{Pqual}$ with a given quality. The algorithm for the synthesis of a mathematical model that describes the relationship of the coating qualitative properties with its parameters is presented in the diagram (Fig. 2).

Regression, neural network, neuro-fuzzy models, decision trees, etc. can be used as models describing functional dependencies. [7]. The PEO process is associated with a long processing time and the need to prepare various electrolytes; therefore, obtaining a large data sample is often limited by time and material considerations. Coating studies for the identification of quality properties and their evaluation is also laborious.

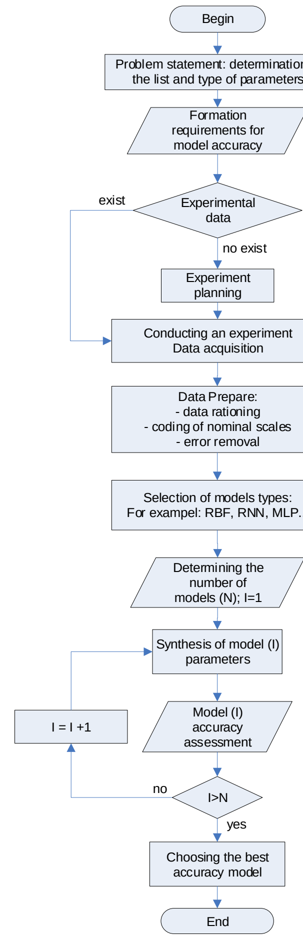

Fig. 2: Model synthesis algorithm

A task requiring substantial material, time and resource costs for research. Thus, one of the essential features, which imposes restrictions on the types of models used and methods for their synthesis, is the number of sets of experimental data, which usually does not exceed a few dozen.

Nowadays, neural networks are becoming increasingly common due to their versatility and flexibility. For example, the following neural network models are used for multi-criteria approximation on noisy data: RBF (Radial Basis Function), GRNN (General Regression Neural Network) and MLP (Multilayer perceptron, class of Feed Forward Neural Network).When it is necessary to perform a partial data extrapolation, to ensure the recovery of data gaps and to work in the conditions where the nature of dependencies is difficult to assume in advance, it is preferable to use MLP based on a multilayer perceptron.

After selecting the type of model, data is prepared to make it suitable for use in a particular model. For neural network models, it is the elimination of data errors, normalization of variable values, conversion of nominal variables, etc.

The next step is to assess the accuracy of the models on the experimental data set. At this stage, it may turn out that some models do not meet the accuracy criteria that were set at the stage of setting the modeling problem. In this case, one can resort to various methods of improving the model accuracy: adjusting the parameters, optimizing the structure. If more than one model cannot provide the specified requirements, then they either fulfill or attenuate the model accuracy requirements or carry out additional experiments to obtain additional data blocks.

We define a complete vector describing the coating parameters (Table 1), which are available for measurement or evaluation as follows:

$$\overline{\mathrm{Pcoat}} = \{\mathrm{Pc}_1, \mathrm{Pc}_2, \cdots, \mathrm{Pc}_n\},$$

where Pc_i– variable describing a specific property of the coating.

Table 1: Main model parameters.

Coating parameters (P_{coat})	**Quality parameters (P_{qual})**
Coating color	Wear resistance
Presence of a transition layer	Crack resistance
Presence of through pores	Resistivity
Degree of crack development	Electrical strength
Uniform appearance of the coating	Specific capacity
Color shade	Dielectric loss tangent
Pore uniformity in the coating thickness	Electrochemical coefficient
Etching degree of the base material	Friction features
Average crack length	Reflection coefficient
Average pore size	Absorption coefficient at a specific wavelength
Elemental composition of the coating thickness	Corrosion resistance
Phase composition of the coating thickness	Compressive strength
Average layer thickness	Thermal conductivity coefficient
Coating adhesion strength to the base	Thermal shock resistance
Specific coating density	Thermal cycling resistance
Coating micro density	and others

Then, we define a vector that will enable or disable a certain parameter in the computational model (since not all parameters may be needed or taken into account in the model):

$$\overline{\mathrm{Pc\_en}} = \{\mathrm{Pc\_en}_1, \mathrm{Pc\_en}_2, \cdots, \mathrm{Pc\_en}_n\},$$

where $\mathrm{Pc\_en}_i$ - coefficient taking the value of 1, if i parameter is taken into account in the model and 0 - if not. Then the element-wise vector production $\overline{\mathrm{Pcoat}} \circ \overline{\mathrm{Pc\_en}}$ will give us the set of coating parameters under study.

A vector describing all the quality indicators and the indicator vector in the model, respectively:

$$\overline{\mathrm{Pqual}} = \{\mathrm{Pq}_1, \mathrm{Pq}_2, \cdots, \mathrm{Pq}_k\};$$

$$\overline{\mathrm{Pq\_en}} = \{\mathrm{Pq\_en}_1, \mathrm{Pq\_en}_2, \cdots, \mathrm{Pq\_en}_k\}.$$

The element-wise vector production $\overline{\mathrm{Pqual}} \circ \overline{\mathrm{Pq\_en}}$ will describe a given set of qualitative properties.

Parameters can be presented in different scales, which can also be determined by the problem conditions. The next step is to bring the nominal and ordinal scales into numerical scales or to perform the coding of "1-of-N" type. For the values that are defined in interval and absolute scales, it is necessary to perform the rationing and centering of the data using the "min/max" method or perform a Z-normalization.

To eliminate errors that may occur in the experimental data, it is proposed to use the methods of statistical data analysis with the subsequent deletion of the invalid data. To do this, we construct the matrix {T} of the Student's t-test values calculated for the case when one data block in the sample is missing:

$$T = \begin{bmatrix} t_{1,1}, t_{1,2}, \cdots, t_{1,n} \\ t_{2,1}, t_{2,1}, \cdots, t_{2,n} \\ \cdots \cdots \cdots \cdots \\ t_{l,1}, t_{l,2}, \cdots, t_{l,n} \end{bmatrix},$$

where $t_{l,n}$ - Student's t-coefficient estimate when excluding from the sample of l data block (row) for the nth parameter (column), l - total number of data blocks. The data block l(row) will be recognized as an error and removed from the sample, if the calculated meaning of the value $t_{l,n}$ differs significantly from the average value calculated for the entire data sample and such a difference will take place only for one of the parameters in the line land will not be observed for any other parameter in the same line. In this case, it can be assumed that the deviation of this parameter is caused by a measurement error or a random factor, and not by any regularity in the data. This can happen as a result of the effects of random factors, for example, error in measuring the thickness of the coating in one of the experiments.

At the next stage, it is necessary to determine the types and structures of neural networks and their adjustable parameters. For example, we need to specify the number of input and output neurons (usually corresponds to the number of input and output parameters of the model), the number of hidden layers, and the activation functions of perceptrons for each of the network layers for an MLP network. The determination of network parameters and their types for such tasks is described in detail in [8, 9, 10].

To assess the accuracy of each of the models under consideration, we write the error vector in the form of:

$$\overline{\mathrm{Pcoat\_error}_j} = \{\Delta\mathrm{Pc}_{1,j}, \Delta\mathrm{Pc}_{2,j}, \cdots, \Delta\mathrm{Pc}_{n,j}\},$$

where j - number of the data block (j = 0 ... l), and the error for each vector component on j is equal to

$\Delta Pc_{i,j} = Pc_{i,j} - \widehat{Pc_{i,j}}$, where $\widehat{Pc_{i,j}}$ - estimated value, i - parameter number in the vector $i = 0 \ldots n$). To estimate the accuracy of the model prediction, we use the values of expectation and variance of the errors calculated for each of the vector parameters:

$$M(\Delta Pc_i) = \frac{1}{n}\sum_{j=1}^{n} \Delta Pc_{i,j};$$
$$D(\Delta Pc_i) = \frac{1}{n}\sum_{j=1}^{n}(\Delta Pc_j - M(\Delta Pc_j))^2.$$

Using cross-validation, one can evaluate the generalizing ability of each of the models, for which we use cross-validation for individual objects (leave-one-out CV). From the initial data sample, we will alternately remove one of the data blocks and train the neural network, and then build a matrix of the obtained values of mathematical expectations and variances:

$$M_k = \begin{bmatrix} M(\Delta Pc_{1,1}), M(\Delta Pc_{1,2}), \cdots, M(\Delta Pc_{1,n}) \\ M(\Delta Pc_{2,1}), M(\Delta Pc_{2,2}), \cdots, M(\Delta Pc_{2,n}) \\ \cdots \quad \cdots \quad \cdots \quad \cdots \\ M(\Delta Pc_{l,1}), M(\Delta Pc_{l,2}), \ldots, M(\Delta Pc_{l,m}) \end{bmatrix};$$
$$D_k = \begin{bmatrix} D(\Delta Pc_{1,1}), D(\Delta Pc_{1,2}), \cdots, D(\Delta Pc_{1,n}) \\ D(\Delta Pc_{2,1}), D(\Delta Pc_{2,2}), \cdots, D(\Delta Pc_{2,n}) \\ \cdots \quad \cdots \quad \cdots \quad \cdots \\ D(\Delta Pc_{l,1}), D(\Delta Pc_{l,2}), \ldots, D(\Delta Pc_{l,m}) \end{bmatrix},$$

where k- serial number of the model.

$$M_{k,i} = \frac{\sum_{j=1}^{l} M(\Delta Pc_{j,i})}{l}, D_{k,i} = \frac{\sum_{j=1}^{l} D(\Delta Pc_{j,i})}{l}.$$

Then the average value $M_{k,i} D_{k,i}$ calculated for each of the columns of the matrices {Mk} and {Dk} will be the expectation and variance of the parameter error for each of the k estimated models.

Each of the models created with a particular quality will fulfill the tasks of multi-criteria approximation. To select the model that is best suited for solving a particular problem, it is necessary to determine the method of decision making. For example, a weighted sum method [11] can be one of the simplest methods to make a decision under certainty. To use it, we set the weight vector (the importance of each parameter):

$$\overline{Wcoat} = \{w_1, w_2, \cdots, w_n\}.$$

Let n criteria be used for evaluating outcomes (corresponds to the number of coating parameters in the output vector or less), and the larger value of the criterion is preferable to the smaller one. We express the alternative evaluation as a weighted sum of the standard deviation of the set of parameters:

$$U_k = \sum_{i=1}^{n} W_i \cdot \left(\frac{1}{M_{k,i}}\right).$$

Then the best alternative would be a model whose criterion value is maximum $k\,|\max(U_k)$).

III. DISCUSSION

As a result of the system analysis, quality indicators and coating parameters were systematized, which allows significantly improving the process of obtaining coatings with the necessary properties by displaying "quality properties - coating parameters". We specified the pre-processing procedure for eliminating gross errors. We proposed the algorithms for choosing a rational model from a number of alternatives.

IV. CONCLUSION

An algorithm for the transition from the vector of coating quality properties to the vector of coating parameters is proposed. The construction and selection of the model will be performed on the basis of experimental data, which are prepared in such a way as to eliminate gross errors. The described method makes it possible to carry out the synthesis of the necessary parameters of the electric mode and the electrolyte parameters in the PEO process based on the vector of coating quality indicators.

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