Application of neural network modeling and fuzzy inference methods in cladding operation design

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Abstract. The article considers an example of a combined approach in the technological operation designing. The features of this approach are considered when choosing and calculating the design and technological parameters of the operation. The proposed method combines the use of the analytical and experimental studies results with soft computing. The example of multi-stage iterative designing of the cladding operation shows how to simplify it. The application of neural network and fuzzy modeling is considered in terms of expanding the possibilities of working with data obtained from analytical and experimental studies. Combining neural network and fuzzy modeling makes it possible to dispense with a minimum amount of data to obtain working dependencies. Such a combined application of the methods provides high accuracy of output data forecasting. Due to the high generalizing ability, the possibility of adaptation and adjustment, the proposed approach allows to expand technological capabilities in the design of operations, to increase the efficiency and competitiveness of production.

1. Introduction
Assignment of processing technological modes is a multivariate nontrivial task. The use of reference data, analytical formulas with all the relative complexity of their use does not guarantee the necessary result. This is due to averaging and uncertainty of data, simplification of formulas for calculation. The choice of processing parameters is made from a range of values which sometimes quite wide. In small batch production with simplified design a limited set of parameters is used related to the effectiveness of operations. For example, when calculating the cutting speed by the formula, only the tool life, which can be considered as limitation, is included in it. The initial calculations do not take into account the efficiency criteria related to economic profitability, ensuring accuracy, quality of processing, what is necessary, for example, with an expert assessment of the car maintainability [1]. To achieve these performance criteria, it is additionally necessary to optimize the modes based on any modeling. With a multi-criteria approach, the task becomes more complicated.

2. Relevance
Currently, when assigning technological modes, an iterative procedure or selection method is used (figure 1). Having assigned the parameters, it is necessary to check any criteria:
- if these criteria satisfy the conditions – the choice is completed;
- if these criteria do not satisfy the conditions, the procedure is repeated with a change in any technological parameters.

**Figure 1.** Block diagram of the algorithm for selecting the rational cladding modes: $\sigma_{\text{max}}$ is maximum stresses in the flexible piles, MPa; $[\sigma_i]$ is endurance limit at asymmetric cycle, MPa; $\theta_{\text{mcm}}$ is melting point of coating material element, °C; $t_0$ is the time of physic-chemical interaction of the particle with the base material, s; $E_k$ is the coefficient of mechanical activation, J; $E_a$ is the energy of thermal activation, J; $\theta_k$ is the contact temperature, °C; $K_{\text{exp}}$ is optimal parameter of relative wear resistance.

When designing a technological cladding operation [2-7], five separate steps are required. At each stage, taking into account the specified processing conditions in the form of the material of the part, the shape of the surface being treated, the possible or required coating material, the technical requirements for the coating, the range of possible equipment and tool, as well as the parameters found in the previous steps, it is necessary to determine the necessary operation parameters. Each calculation method is based on a result obtained from an experimental or analytical relationship. Each of them corresponds to specific conditions, which may not coincide with the production conditions for which current designing is carried out. To determine or refine certain parameters, it may be necessary to carry out a laborious process of modeling a specific situation, for example, by the finite element method. For this, in turn, additional studies or calculations may also be necessary.

When processing data at all or individual stages of operation designing by means of soft computing, supplemented by neural network modeling, the final process can be greatly simplified. Such fuzzy models are characterized by flexibility, the ability to adjust the parameters for the changed processing conditions on the basis of data obtained during real processing or using expert polling. This type of designing for modern wide-range production with small and medium-sized series of launched products is relevant.

The paper [8] shows the classic way of using ANFIS. On the basis of experimental cutting forces collected during turning under certain conditions, a model is formed. Technological modes are used as input vector, the cutting force as the output one. A fuzzy inference system is generated that accurately predicts the turning force. Modeling capabilities can be extended to suit the specific situation. For example, when processing composite materials, the cutting force is affected by particle size. This parameter is added as an input factor to the processing modes input, to predict surface roughness and
cutting forces in [9].

The article [10] considers the ANFIS system to predict roughness by process parameters at the designing stage of the operation. In addition, the processing modes are then optimized by the genetic algorithm according to the criteria of laboriousness and productivity. After processing, the actual roughness is determined from the digital image of the machining surface also with the help of ANFIS.

The combined approach of using neural networks and fuzzy logic is shown in [11].

3. Experiment technic

In light of the foregoing, the basis for the functioning of computer-aided design systems should include expert systems constructed by the method of solving inverse problems. This makes it possible to assign modes, starting from the necessary parameters for accuracy and quality. To do this, the input data selects the specified surface characteristics, economic efficiency parameters. The output of such a system will be the recommended technological parameters in the form of a range of acceptable values. This will make it possible to carry out further additional conclusions related to various restrictions, for example, the availability of tools, equipment, etc. An example of such a system is the model given in [6], where it allows you to determine the range of acceptable values of the processing characteristics.

The construction of such a system is based on a fuzzy knowledge base. For this, based on a survey of an expert/experts, analysis of theoretical and empirical studies, a generalized map of conditions is made in the form of linguistic rules “IF .. THEN ..”. Based on such a rule base, a fuzzy inference system is formed. The input to it can be, for example, the coating thickness, tool and workpiece parameters, processing time, maximum permissible loads. The output is the processing mode parameters.

The output parameters that determine the processing efficiency depend on a set of characteristics. In the study of the relationships of interest to us, not all of them are taken into account. When coating by cladding, for example, one of the main indicators is the thickness of the coating.

So, figure 2 shows the dependence of the coating thickness \( h \) on varying the diameter \( d \) of the pile of the tool (0.14-0.18 mm) and the ratio of the length \( l \) of the departure of the pile to the radius \( r \) of its fixing (0.25-0.35) with an interference fit of 1 mm and the ratio of angular rotational speeds of the processed sample and flexible tool – 0.00225. The thickness of the formed coatings was estimated by means of a four-factor experiment, set according to the Box-Benkin plan [12].

![Graph](image1)

**Figure 2.** Graph of the thickness of the coating with a change in the diameter of the pile of the tool and the ratio of the length of the departure of the pile to the radius of its fixing: a – experimental studies, b - ANFIS simulation result.

Hybrid fuzzy networks are widely used to approximate nonlinear dependencies of any complexity, noisiness, and uncertainty. In our case, ANFIS hybrid fuzzy inference network is used for parameter analysis by the Sugeno method. The training method is hybrid. The number and type of functions and
input parameters were selected according to the minimum learning error. With the help of this network the rule base is formed for the selected input parameters.

The neural network used in this example is a two-layer feed-forward network with a Levenberg-Marquardt learning algorithm.

For example, a model is modified to describe the dependence of the coating thickness when changing the diameter of the pile of the tool and the ratio of the length of the pile to the radius of its embedment. Using the control points obtained during the experiment or analytical calculation as training dataset, the fuzzy neural network ANFIS is formed. It corresponds to a specific relative feed rate and brush rotation speed and interference fit. Then, using the extended vector of input values, for two inputs, the pile diameter and the relative length of the pile, the result is generated - the thickness of the coating. It turns out an expanded set of new training data. If the initial set was 30 points, then using ANFIS 200 points are already obtained. If necessary, the number of input parameters can increase and the rules can be modified based on an expert survey or the results of additional experiments. This will expand the possibilities for the selection of technological parameters in the range of possible applications and in their number. After this, the neural network is trained with the choice of its parameters, the number of layers and neurons, the type of activation function, the learning speed parameter to achieve the minimum error. An example of the obtained and initial surface is shown in the graphs in figure 2.

Another example is the total bending moment acting on the wire element in the contact zone of the tool and the workpiece. When cladding in specific processing conditions, this moment depends on a whole range of conditions. These include coating material, workpiece material, interference fit, the length of the bending part of the pile, the radius of the fixing, the diameter of the pile, the width of the brush and its fill ratio.

So, for example, figures 3, 4 shows the dependences of stresses on the length of the bending part of the pile during sliding during cladding, expressed through the angle $\gamma$, which determines the position of the flexible element in the contact zone with the following technological parameters: tool pile $d=0.2$ mm, radius of the embedment – 100 mm; cladding material – tin bronze; diameter of the workpiece – 200 mm; interference fit – 1.5 mm; $l=25$-100 mm.

![Figure 3. Stresses in flexible elements depending on the length of the bending part of the pile along the contact zone: grid graph – results of CAE modeling; bar graph – results of analytical calculation according to the mathematical model algorithm.](image1)

![Figure 4. The resulting output surface for the control points in the ANFIS system for stresses in flexible elements depending on the angle of bending of the wire ($x_1$) and pile overhang ($x_2$) for normalized data.](image2)
4. Results
The results of neural network training for the initial data obtained from control points give an error of 8%. Using a limited set of data, ANFIS was trained, which forms a fuzzy inference system (figure 5) which the output surfaces shown in figure 4.

![Figure 5. The structure of the two input fuzzy inference system.](image)

An example of membership functions of the input parameter – $x_i$ – wire bending angle is shown in figure 6.

![Figure 6. Membership functions for pile bending angle.](image)

The training data set was generated by the ANFIS system. Already through it, a feed-forward neural network was trained. The result of checking the accuracy for the neural network using the test source data developed on the basis of the set generated by the fuzzy system was showed an almost zero error. The error in training this network according to the data obtained after a fuzzy system was 0.001%.

5. Conclusions
The use of artificial intelligence methods, in particular soft computing and neural network modeling, greatly simplifies the design cycle of technological operations. Using the complex of these methods, it is possible to integrate the results of analytical calculations, including the finite element method and the results of experimental studies supplementing the obtained models with information from expert surveys. This allows the iterative procedure for the selection of structural and technological parameters to be carried out faster with high accuracy in predicting the desired output parameters. Such methods make it possible to integrate optimization procedures into the designing process, including solving multicriteria problems.

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