A combined method for designing operations using soft computing

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Abstract. The article considers the possibility and features of shared use of two approaches of modern artificial intelligence: neural networks and fuzzy logic. Taking into account the advantages and disadvantages of each of the methods considered, the method of sequential use of these systems is considered. Fuzzy systems can be used for the initial creation of an expert inference system with its subsequent adjustment by optimization methods. It is possible to use the formation of a fuzzy inference system based on a hybrid neural net inference system based on control points obtained analytically or experimentally, followed by the generation of dataset for training neural networks. The use of these methods together increases the speed of operation designing, reliability of output, flexibility of approach to the choice of parameters, expansion of capabilities in production environments characterized by a wide variety of operations, materials, processing methods. An example of using this approach for the cladding method is given.

1. Introduction

For modern production, characterized by great flexibility due to constant upgrades and changes in manufactured products, small series, short production times, the task of reliable and quick design of technological operations is relevant. Moreover, the quality of the proposed technological solutions must meet the highest requirements. For this, it is necessary to widely apply multicriteria optimization methods, to take into account the complex interrelations of operational, structural and technological parameters. Moreover, less time is being devoted to working out and identifying all of these relationships and the complexity of design and research work is growing.

For this reason, neural networks and soft computing methods are increasingly being used.

2. Relevance

A method for the joint use of a neural network and a fuzzy inference system is known. To form the training data necessary to create a fuzzy output system, a neural network is used, which creates output in the form of upper, lower boundaries and the most probable value. The paper [1] shows an example of the use of a sequentially neural network that is trained on a small data set and a fuzzy output system. After that, a trained neural network generates a large amount of data to form a fuzzy output system. In a similar study [2], the same result in the form of limit boundaries and the most probable
value is achieved using a fuzzy output system. This approach allows the boundaries of deviations with the most probable value of the modeled parameter to be established, which is more approximate to real processes with random output.

For multicriteria optimization of the turning process, the fuzzy system can be used to derive a comprehensive optimization criterion, which includes cutting force, roughness and productivity. Based on the optimal value, the corresponding levels of input controlled technological factors are found [3].

To increase the efficiency of designing operations, a complex of models can be used. For example, four different neural networks are used to increase output reliability when determining tool wear. A general conclusion is made as a result of a generalized assessment [4].

In [5] genetic algorithms were used to set up a fuzzy knowledge base in order to predict roughness during ultraprecise turning with input parameters - cutting conditions.

The article [6] shows an example of using a fuzzy output system based on the MAMDANI method, where cutting force is added to the input vector, the output is tool wear. Comparison of fuzzy inference, neural network and regression method showed a significant advantage of the first two at their comparable level relative to each other.

The paper [7] gives an example of the successful joint use of fuzzy output with RSM. To build the RSM model, data generated using the fuzzy system is used to reduce additional expensive experimental studies.

3. Experiment technic
To work with the necessary dependencies, it is proposed to use two different modeling methods. The first is a soft computing, including neural fuzzy networks, the second is a neural multilayer network.

To approximate nonlinear dependencies, the ANFIS hybrid network is used for fuzzy inference by the Sugeno method (figure 1).

![Figure 1. Block diagram of the ANFIS system.](image)

The methodology for setting the parameters of this system is an iterative procedure for determining the parameters of a fuzzy logic inference system using a hybrid algorithm. It adjusts the parameters of membership functions for input variables and the value of weighting coefficients for the conclusions of linguistic rules. The learning algorithm itself is a combination of the backpropagation method and the least squares method. The network has five layers. Input (in the example, the length of the bending part of the pile and the angle of bending when it passes through the processing zone), each is divided into a certain number of terms - membership functions. Their number can be set usually in the range from 2 to 7. The shape of the selected membership functions is a bell-shaped curve, which is defined by the formula:

\[
\mu_{k,j}(x_i) = \frac{1}{1 + \left|\frac{x_i - c}{a}\right|^{2b}},
\]  

(1)
where $a$, $b$, $c$ are the configurable parameters of the membership function; $j$ is the number of terms. In the second layer, the number of nodes corresponds to the number of rules. These rules are formulated in the form of fuzzy linguistic conclusions of the type "IF... - THEN...", which fully reflect the influence of changes in the input vector $x$ on the output vector $y$. The output of the second layer yields the degree of fulfillment of each of the rules $m$ by the formula:

$$w_m = \mu_{1,n}(V) \times \mu_{2,l}(S) \times \mu_{3,p}(t),$$

where $n$, $l$, $p$ are the numbers of the corresponding membership functions in each of the rules. In this expression, $t$- norm is executing when performing the operation "AND". In the third layer, the number of nodes is again equal to the number of rules. Each node determines the relative degree of rule execution.

$$\bar{w}_m = \frac{w_m}{\sum_{v=1}^{m} w_v}$$

In each of the nodes of the fourth layer, the number of which remains equal to $m$, the contribution of each fuzzy rule to the network output is calculated:

$$y = b_{m,0} + b_{m,1} + b_{m,2},$$

where $b_{m,k}$ are the configurable coefficients. In the output layer, the contributions of all the rules are summed.

$$y = y_1 + y_2$$

The process of adjusting the parameters of the first and fourth layers is terminated when the required learning error is reached or after the specified number of training epochs is completed.

The neural network selected for use is the feed-forward neural network. The block diagram of the network is shown in figure 2. It has two layers. The input vector includes two parameters (the angle of bending of the pile and the diameter of the pile), the output is the magnitude of the stresses. In the first layer, the number of neurons varied from 5 to 15. The best learning result was obtained with 7 neurons with a sigmoid activation function. The output is one neuron with a linear activation function.

The fuzzy system was trained according to the dependences obtained in the course of analytical calculations, supplemented by the results of CAE-modeling. Then the selected neural network was trained. Plot regression is shown in figure 3.

Fuzzy systems can be used to expertly configure complex dependencies in manual mode using the Mamdani method.

4. Results
For example, figure 4 shows the output surfaces for the dependences of the cladding power on a set of parameters (embedment radius, interference fit, pile diameter, pile overhang). Dataset was formed on the basis of information from individual dependencies. To reduce the error, the initial conclusions
obtained and the settings for the membership functions of the output system are set according to control points.

![Figure 3. Plot regression errors for model test data using a neural network.](image)

**Figure 3.** Plot regression errors for model test data using a neural network.

![Figure 4. The result of manual adjustment of the dependence of the processing power on the interference fit and the radius of the fictitious embedment by the Mamdani method.](image)

**Figure 4.** The result of manual adjustment of the dependence of the processing power on the interference fit and the radius of the fictitious embedment by the Mamdani method.

Using a limited data set (24 test points) to approximate the dependence of the stresses in the pile gives an error of 8%. When using a limited data set for training the ANFIS fuzzy inference system, the error was about 2%.

After the formation of the vector of input values, varying over the entire allowable range with various combinations in the amount of 200 points, the corresponding output values are made. After that, these data were used to train the neural network. Testing on a control dataset taken from analytical results gives an error of less than 1% (figure 3).

The resulting system of fuzzy inference after training is reflected in the linguistic rules of inference. The system of linguistic rules for the selected number of input membership functions is obtained:

1. If \( (x \text{ is in } 1mf1) \text{ and } (y \text{ is in } 2mf1) \) then \( \text{output is out1mf1} \) (1).
2. If \( (x \text{ is in } 1mf1) \text{ and } (y \text{ is in } 2mf2) \) then \( \text{output is out1mf2} \) (1).
3. If \( (x \text{ is in } 1mf1) \text{ and } (y \text{ is in } 2mf3) \) then \( \text{output is out1mf3} \) (1).
4. If \( (x \text{ is in } 1mf2) \text{ and } (y \text{ is in } 2mf1) \) then \( \text{output is out1mf4} \) (1).
5. If \((x\text{ is in} \text{mf}_1)\) and \((y\text{ is in} \text{mf}_2)\) then \((\text{output is} \text{out}_1 \text{mf}_5)\) (1).
6. If \((x\text{ is in} \text{mf}_1)\) and \((y\text{ is in} \text{mf}_3)\) then \((\text{output is} \text{out}_1 \text{mf}_6)\) (1).
7. If \((x\text{ is in} \text{mf}_3)\) and \((y\text{ is in} \text{mf}_1)\) then \((\text{output is} \text{out}_1 \text{mf}_7)\) (1).
8. If \((x\text{ is in} \text{mf}_3)\) and \((y\text{ is in} \text{mf}_2)\) then \((\text{output is} \text{out}_1 \text{mf}_8)\) (1).
9. If \((x\text{ is in} \text{mf}_3)\) and \((y\text{ is in} \text{mf}_3)\) then \((\text{output is} \text{out}_1 \text{mf}_9)\) (1).

The parameters of the output membership functions are the coefficient values:

- \(m_{F1} = [-833.2 \ 783 \ 752.6] \)
- \(m_{F2} = [-746.2 \ 126.4 \ 443.1] \)
- \(m_{F3} = [-169.3 \ 108.6 \ 48.54] \)
- \(m_{F4} = [1.824 \ -199.4 \ 52.32] \)
- \(m_{F5} = [199.4 \ -107.2 \ 264.7] \)
- \(m_{F6} = [91.6 \ -406.7 \ 476.9] \)
- \(m_{F7} = [72.11 \ -77.36 \ -3.244] \)
- \(m_{F8} = [189.9 \ -27.05 \ -81.29] \)
- \(m_{F9} = [112.8 \ -59.68 \ 0.9131] \)

This makes the influence of input factors on the output transparent. The learning outcome is also available in the form of three-dimensional output surfaces (figure 4).

5. Conclusions
The use of modern modeling methods significantly expands the possibilities for the design of technological operations. The joint use of neural networks, fuzzy inference systems, analytical and experimental research methods allows for a variety of preparatory work in the design of operations. Moreover, for a variety of production conditions, it is possible to quickly adapt existing models to specify technological modes and perform their optimization. Moreover, the choice is not limited only to the purpose of the technological regime, but also allows you to determine a variety of other related design and technological conditions, as can be seen from the example considered when applying the cladding method.

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