Prediction of Valves Technical Condition Using Neural Network Models

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Abstract. An approach to predicting the technical state of reinforcement based on the use of artificial neuro-fuzzy networks, which allow predicting the value of the predicted value, taking into account external factors, such as operating conditions and wear and tear.

1. Introduction

During operation valves are subjected to impacts of a considerable number of factors which in many cases are incidental (variation of working and ambient parameters). As a consequence, this leads to the scattering of valves technical condition parameters. At that, the more technical condition parameters vary, the less effective the scheduled maintenance and repair schemes (M&R) are, since in this case there is always a factor of object technical condition uncertainty [1].

Solving diagnostic problems is intimately connected with reliability prediction for the nearest period of operation, until the next technical inspection, overhaul, etc. In connection with the increasing role of automatic and automated systems the significance of their condition prediction is increasing as well. Without prediction it is difficult to control the system condition and impossible to prevent emergencies in a timely manner. Implementation of theory and methods of prediction in items reliability analysis makes it possible to significantly increase the effectiveness of their reliability evaluation at different stages of development, fabrication and operation.

The advent of technical systems executing responsible functions results in the increasing role of technical condition prediction at some period of time in the future allowing for timely actions to prevent failures. During technological development process the problem of technical condition control by timely switching to backup, well-timed transition to new operation modes, etc., has appeared. Thus, new stages of technological development led to a new technical challenge – the prediction of technical condition.

Depending on the predicted parameters and the target trend of prediction, available methods and mathematical tools are selected.

Class multitude and size are defined by specific technical features of the predicted objects. The methods based on assignment of investigated objects to one of the classes will be referred to as methods of statistical classification. Apparatus of pattern recognition theory as well as of artificial neural networks theory is used in these methods.

2. Prediction using hybrid neural network

Recognition algorithms in technical diagnostics are partly based on diagnostic models which establish a connection between the technical system conditions and their display in the diagnostic...
signals space. Rules for decision-making (decision rules) appear as an important part of recognition issue. Solving a diagnostic problem, recognizing the item as fault-free or faulty is always connected with the risk of false alarm or target skip.

Fuzzy neural network is a multilayer neural network of special open-loop structure where usual (non-fuzzy) signals, weights and activation functions are used, and the execution of summing operation is based on the use of fixed T-norm, T-conorm or some other continuous operation. At that, the values of neural network inputs, outputs and weights are real numbers from interval $0 – 1$ [2].

The purpose of fuzzy neural networks is knowledge extraction for implementation of fuzzy rules on the basis of neural networks. Such approach helps to compensate for one of the main disadvantages of neural networks, i.e. the neural network response is nontransparent. Neural network itself is a black box, i.e. the response cannot be explained. This approach makes it possible to implement explanation function for neural networks.

Application of artificial fuzzy neural network apparatus appears to be a promising trend for solving prediction problems.

Fuzzy neural, or hybrid, networks are designated to combine the advantages of neural networks and fuzzy inference systems. On one hand, they allow to develop and present system models in form of fuzzy production rules which possess clarity and simplicity of informative interpretation. On the other hand, neural network methods are used to build fuzzy production rules, which is a more convenient and less labor-intensive process for system analysts [3].

The main idea underlying the model of hybrid networks consists in using available data sampling to define membership function parameters which best correspond to some fuzzy inference system. At that, known neural network training procedures are used for passage of membership function parameters [4].

A hybrid network is trained using error backpropagation algorithm. This algorithm represents an iterative gradient algorithm of minimization of mean square deviation of output values from desired values (error minimization) in multilayer neural networks.

Let us develop a fuzzy model of hybrid network for prediction of gate valve technical condition. The essence of this problem is to predict the system condition values for a defined future moment knowing the dynamics of the system condition change within a fixed time interval.

Traditionally, various models of technical analysis based on the use of various indicators are applied for solving this problem. At the same time, the presence of implicit trends in the dynamics of technical condition change makes it possible to use the model of adaptive fuzzy neural networks.

Let us use the information on the change dynamics of gate valve technical condition within some time interval as the input data. Figure 1 shows the dynamics of gate valve model condition for 10 years of operation, the step of gate valve technical condition check is 3 months. The graph is constructed based on the observation results of gate valve technical condition. It should be noted that during the assessment of system technical condition several factors affecting the system condition have been used (leakage through the gate valve, actuation time, leakage in relation to ambient medium, etc.), and annual preventive maintenance and a once-every-three-years planned maintenance are also taken into account [5].
Figure 1. Dynamics of gate valve technical condition over 120 months

For further data use let us perform the graph digitization and present the dynamics in Table 1.

Table 1

| No. | T, months | sys | No. | T, months | sys |
|-----|-----------|-----|-----|-----------|-----|
| 1   | 2         | 3   | 4   | 5         | 6   |
| 1   | 0         | 1   | 21  | 60        | 0.954 |
| 2   | 3         | 0.997 | 22  | 63        | 0.96 |
| 3   | 6         | 0.994 | 23  | 66        | 0.952 |
| 4   | 9         | 0.991 | 24  | 69        | 0.944 |
| 5   | 12        | 0.988 | 25  | 72        | 0.936 |
| 6   | 15        | 0.992 | 26  | 75        | 0.969 |
| 7   | 18        | 0.988 | 27  | 78        | 0.96 |
| 8   | 21        | 0.984 | 28  | 81        | 0.951 |
| 9   | 24        | 0.98 | 29  | 84        | 0.942 |
| 10  | 27        | 0.985 | 30  | 87        | 0.95 |
| 11  | 30        | 0.98 | 31  | 90        | 0.94 |
| 12  | 33        | 0.975 | 32  | 93        | 0.93 |
| 13  | 36        | 0.97 | 33  | 96        | 0.92 |
| 14  | 39        | 0.988 | 34  | 99        | 0.929 |
| 15  | 42        | 0.982 | 35  | 102       | 0.918 |
| 16  | 45        | 0.976 | 36  | 105       | 0.907 |
| 17  | 48        | 0.97 | 37  | 108       | 0.896 |
| 18  | 51        | 0.975 | 38  | 111       | 0.939 |
| 19  | 54        | 0.968 | 39  | 114       | 0.927 |
| 20  | 57        | 0.961 | 40  | 117       | 0.915 |
Let us assume that a fuzzy model of hybrid network will contain 4 input variables. At that, the 1st variable will correspond to current time, the 2nd variable – to previous time (t-1), the 3rd variable – to time (t-2), and the last variable – to time (t-3).

Before generation of Sugeno fuzzy inference system structure, after calling the properties dialog box, let us set 3 linguistic terms for each input variable and choose triangular (hat) functions as the type of their membership functions.

To train a hybrid network let us use a hybrid training method with an error level of 0 and number of training cycles set as 10. After the hybrid network has completed its training, we will analyze the graph of training error given in Figure. 2.

![Figure 2. Dependency graph of training error and number of training cycles](image)

The training of the hybrid neural network was completed after the 4th cycle. Graphical visualization of fuzzy model structure is extremely difficult since the number of rules in the developed adaptive system is 81.

Adequacy check on the built fuzzy model of hybrid network is carried out using retrospective prediction of technical condition value for a future moment, e.g. for the 120th month, considering the 108th month as the current one for the present case.

The developed fuzzy model predicts the value of output variable for a time in the future, namely the 120th observation, which equals 0.862.

By comparing the obtained value with the corresponding value in Table 1 equal to 0.903 we can assess the prediction accuracy using formula (1).

$$OO = \frac{|Z(t) - \hat{Z}(t)|}{Z(t)} \cdot 100\%$$

(1)
where \( Z(t) \) is actual value at time \( t \), and \( \hat{Z}(t) \) is predicted value.

Let us calculate a relative prediction error:

\[
OO = \left| \frac{0.756 - 0.792}{0.756} \right| \cdot 100\% = 4.76\% \tag{2}
\]

3. Conclusions

A method for prediction of valves technical condition has been proposed; it is based on the use of artificial fuzzy neural network apparatus which helps to forecast the predicted value with account of external factors, e.g. operating conditions and equipment wear. A fuzzy neural model of hybrid network has been built to predict the technical condition of gate valve. An adequacy check on the built fuzzy model of hybrid network has been carried out using retrospective prediction and it showed the relative prediction error of less than 5%.

4. References

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