Prediction life of lubricants on the analysis of experimental data on their optical density

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Abstract. The paper presents the results in the field of research and analysis of the optical density of motor oil using mathematical and intelligent models. The quadratic approximations of the dependence of optical density on time are obtained for three different temperatures of temperature control. It is established that each curve of the change in optical density with time contains an inflection point. On the basis of which it was hypothesized that these moments correspond to a certain phase transition in the oil under study. A three-dimensional model of dependence of the rate of change of optical density on temperature and test time was also constructed. When analyzing this dependence, the character of the inflection curve is established, which is proposed as an indicator indicating the attainment of the limiting resource of lubricating oils.

Lubricating oils, regardless of their area of application, are usually consumable. The most important characteristic of lubricating oils is the resource. Under the resource usually understand the limit state, on the achievement of which the oil is replaced. It is estimated by the mileage of the vehicle in kilometers traveled or by operating the mechanism in engine hours.

Many studies are devoted to the assessment of the marginal life of lubricants, for example [1], [2], [3], [4], [5], [6], [7]. In practice, to determine the marginal resource of oils are usually guided by the provisions of the regulations established by manufacturers of equipment and technology. In this case, the method of determining the resource consists in the study of operational properties (viscosity, optical properties, evaporation, etc.) in the process of prolonged exposure to high temperatures. For example, in accordance with the STO Gazprom 2-2.4-134-2007, in determining the thermal-oxidative stability, the oil is kept at 180 °C for 3 and 6 hours. Such techniques are imperfect, since they do not take into account the cyclical nature of the process of temperature exposure, limited to the width of the range of exposure to temperature for different operating modes of oils and the time of thermal exposure.

From the point of view of solving practical problems associated with the operation of lubricating oils, there is a need to solve the “inverse problem”. That is, instead of indicating the onset of the limiting state of the oil, it is necessary to estimate the time of its onset and predict the residual resource. In this case, it is possible to propose different approaches to determining the moment of occurrence of the limit state. The first is to establish the fact of reaching the limit state of a certain operational parameter. The second is the study of the dynamics of changes in the parameters characterizing the resource. This paper is devoted to the consideration of this alternative approach to the analysis of the resource of lubricating oils. Justification of the proposed campaign is impossible without experimental studies and their
effective model description.

The aim of the work is to develop a method for predicting the residual life of lubricating oils using the method of neural network modeling of indicators of residual life.

As the main characteristic in the course of the study, optical density was adopted as an integral indicator of the accumulation of total degradation products in the test oil. The direct method of photometric measurement was chosen as the main method for evaluating thermo-oxidative destruction. In previous studies [8], the relationship of optical density with other important indicators characterizing oil life was established.

The studies were conducted on Rosneft Maximum 10W-40 SL/CF, a partially synthetic motor oil. A series of experiments were carried out, which consisted of the following: a sample of constant-weight oil of 100 g was poured into a glass beaker for temperature control and stirred with a glass stirrer with a rotational speed of 300 rpm and tested for 8 hours successively at temperatures of 160, 170 and 180 °C. After every 8 hours of testing at each temperature, a part of the sample was taken (2 g) for direct photometric measurement with a 2 mm thick layer of photometric layer and calculation of the optical density D:

\[
D = \begin{cases} 
\lg \frac{300}{R}, & \text{if } R = 30 \div 300 \\
1, & \text{if } R < 30
\end{cases}
\]

where 300 – is the photometer reading in the absence of oil in the cuvette, μA, R – is the photometer reading when the oxidized oil is filled with the cuvette, μA.

Results are expressed by a series of dependences of optical density on temperature and test time (figure 1).

It is noted that with increasing temperature the rate of growth of optical density increases nonlinearly. It was also noted that each curve of the change in optical density with time (figure 1) contains an inflection point. These points of inflection correspond to the moments of the maximum increase in optical density. You can hypothesize that these moments correspond to a certain phase transition in the oil under study. Thus, they can be taken as an indicator indicating the attainment of a marginal resource. It can also be noted that the inflection moment of the characteristic, as a rule, precedes the moment when the main operational characteristics actually reach the limit values.

Further analysis of the results was carried out by constructing a three-dimensional model of the dependence of the rate of change of optical density on temperature and test time. The model was proposed to be built in the framework of the neural network approach, because a priori information about the process is insufficient, therefore, the model will be based only on measured data. As the source data, we take the differences of neighboring measurements, provided that the time interval between measurements is constant.

Table 1 presents the values of the standard deviation for some variants of the neural network structure.

| Number of neurons | RMS One layer | RMS Two layers, the number of neurons in the second layer with two neurons in the first |
|-------------------|---------------|----------------------------------------------------------------------------------|
| 2                 | 0,0164        | 0,0347                                                                         |
| 3                 | 0,0269        | 0,0785                                                                         |
| 4                 | 0,0729        | 0,0252                                                                         |
| 5                 | 0,0728        | 0,0163                                                                         |
| 6                 | 0,0722        | 0,0205                                                                         |
| 7                 | 0,0741        | 0,0720                                                                         |
The difference in optical density (figure 1) was approximated using a neural network model with Bayesian regularization (the Levenberg-Marquardt training algorithm) [9], which is highly smooth and works well in small training samples. The structure of the model included two hidden layers with one neuron in each. The algorithm for constructing the model is implemented by means of the MATLAB R2017b package.

It should be noted that the minimum error value does not guarantee the adequacy of the model to the process being studied. From the point of view of the qualitative assessment of the model, it can be argued that it describes the intended nature of the process to a much greater extent than the locally quadratic one. The RMS value of the selected model \( W = 0.0347 \).

Analyzing the presented dependence, it can be noted that with such a network configuration, the crest of the peaks of the rate of change of optical density is located linearly in the time-temperature parameters plane (figure 2).

With this model, you can explore the lubricating oil and get a forecast of its resource. Subsequently,
upon receipt of a marketable oil of the same brand, it is possible, having examined the oil only at one
temperature and for a short time, to predict its resource during the whole service life, based on the
reference model.

The results obtained make it possible to take a fresh look at the problem of predicting the residual
life of oils. The approach used is consistent with the current trend of studying complex processes taking
place in technical systems using modern approaches to data analysis and machine learning.

In further studies, it is proposed to pay more attention to the optimization of models comparing the
qualitative and quantitative characteristics of lubricating oils, as well as building speed models based on
the primary smooth model of dependence of optical density on temperature and time, which was
proposed earlier [10]. As a result, it is proposed to clarify the qualitative characteristics of the obtained
velocity model, in particular, the nature of the “ridge” placement.

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