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Identification of qualitative regularities in the functioning of neural network models of a critical resource of lubricating oils

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Abstract. In the present work, it is proposed to compare two approaches to building a model of a critical resource of lubricating oils that describe the rate of change in the optical density of oils with time, depending on the duration and temperature of temperature control. The initial data for building models of a critical resource are the results of measurements of the optical density of oils. The data obtained as a result of experiments are processed using a neural network model with Bayesian regularization, which has high smoothness and works well in conditions of small training samples. In this case, emphasis is placed on the ability of the model to contribute to the mapping of the general laws governing the process of thermo-oxidative destruction for more detailed study. As a result, the approach in which the initial data for the model are calculated values of the differential estimates of the partial derivative obtained from the primary neural network model of optical density is more informative from the point of view of describing the qualitative patterns observed in lubricating oil under high temperatures.

The study of the thermal-oxidative properties of lubricating oils involves a large amount of experiments, during which the oil is aged under the influence of high temperatures, and at certain intervals of time samples are taken and studied. Sample analysis includes studies of direct and indirect indicators of thermal-oxidative destruction [1]. The compilation and analysis of experimental data is an integral stage of the research.

The construction of formal mathematical models is a generally accepted approach used in the analysis of measured data [2-5]. The complexity of the processes occurring in the oil with prolonged temperature exposure, makes it necessary to apply appropriate approaches and methods for constructing models of oil oxidation. The lack of a priori information study of the oxidation process leads to the fact that the use of generally accepted parametric models is difficult because of the impossibility of a rational choice of the parametric structure. Therefore, there is a need to apply the approaches developed in the framework of modern data analysis and machine learning technologies.

This paper proposes a comparison of two approaches to building a model of a critical resource of lubricating oils, describing the rate of change in the optical density of oils with time, depending on the duration and temperature of temperature control. The requirements for the model can be characterized by three qualitative properties:

- adequacy (or accuracy) of the description of the speed parameter;
- smoothness of the model;
- the ability to identify qualitative regularities of the process of thermo-oxidative destruction.

The purpose of the model is to predict the rate of change in optical density for temperatures and durations of thermostating, other than those studied in the process of experimental research.

The initial data for building models of a critical resource are the results of measurements of the optical density of oils. The studies were conducted on Toyota Castle 10W-30 SL commercial all-season mineral engine oil and on Mannol Molibden 10W-40SL / CF partially-synthetic engine 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 ° s 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:

$$D = \begin{cases} \lg \dfrac{300}{R}, if\ R = 30 \div 300 \\ 1, if\ \ \mathrm{R} < 30 \end{cases} \tag{1}$$

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.

The data obtained as a result of the experiments were approximated using a neural network model with Bayesian regularization (Levenberg-Marquardt training algorithm) [5], which has high smoothness and works well in small training samples. The structure of the model included two hidden layers with two neurons in each. The algorithm for constructing the model is also implemented by means of the MATLAB R2017b package. The results of applying the neural network approach to building a model of optical density for oils Toyota Castle 10W-30 SL and Mannol Molibden 10W-40SL/CF are shown in figures 1, 2.

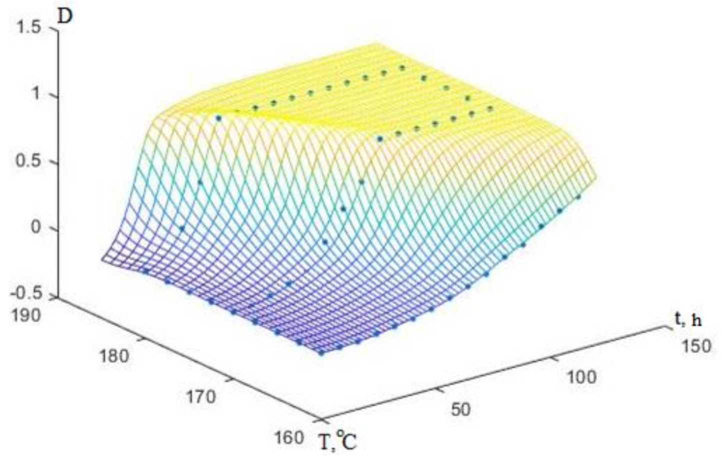

Figure 1. The dependence of optical density on time and temperature test mineral engine oil Toyota Castle 10W-30 SL: 1 - 180 °C; 2 - 170 °C; 3 - 160 °C.

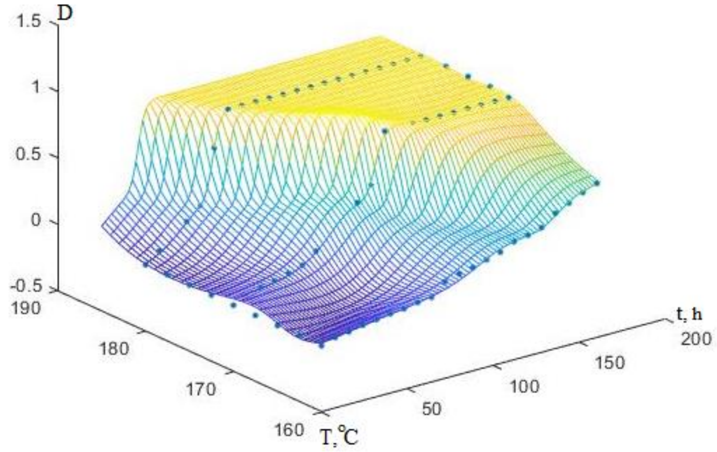

Figure 2. The dependence of optical density on time and temperature test part-synthetic motor oil Mannol Molibden 10W-40SL / CF: 1 - 180 °C; 2 - 170 °C; 3 - 160 °C.

When building a model for predicting the critical oil resource, it was also proposed to use the neural network approach, with the following prerequisites. In previous studies, for example [1, 6], it was noted that the curves of the dependence of optical density on time contain inflection points. These points of inflection correspond to the moments of the maximum increase in optical density. You can put forward the assumption 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 the limiting resource of lubricating oil.

Three-dimensional model analysis with the conclusion that a critical resource is reached by lubricating oil is carried out by localizing the maximum values of the partial derivative $\frac{\partial D}{\partial t}$ in the "time-temperature" space, which, according to the proposal put forward, carry information about the critical value of the residual life of the lubricating oil.

Let us describe the first of the alternative approaches to the construction of a three-dimensional model of the dependence of the rate of change in optical density on temperature and test time. As the source data, we take the differences of neighboring measurements, provided that the time interval between measurements is constant (figure 3, 4).

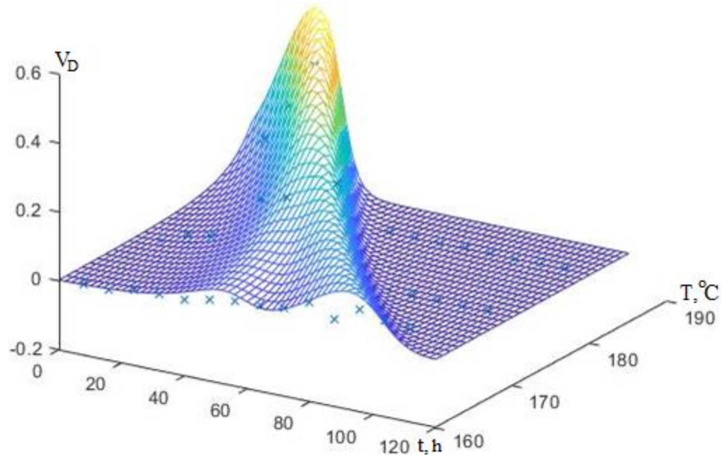

Figure 3. The dependence of the rate of change of optical density on time and temperature as a result of testing of Toyota Castle 10W-30 SL mineral engine oil, built using the first approach.

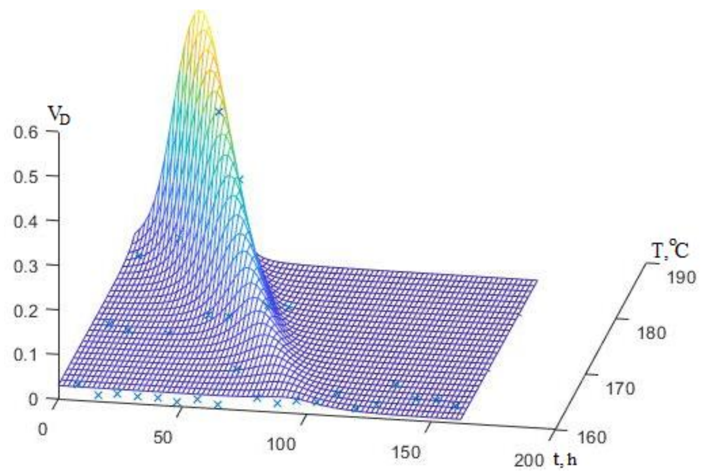

Figure 4. The dependence of the rate of change of optical density on time and temperature as a result of testing the partially synthetic Mannol Molibden 10W-40 motor oil, using the first approach.

Baseline data for building a neural network model of the rate of change in optical density - the difference between adjacent measurements of optical density, provided that Δt = const. The results are presented for the case Δt = 8 hours. Complicating the structure of the model, namely increasing the number of layers in the network and the neurons in them, does not lead to a compromise, that is, to preserve the smoothness of the model and the accuracy of the prediction of the partial derivative.

Let us turn to the second approach, where the source data is the calculated values of the differential estimate of the partial derivative $\frac{\partial D}{\partial t}$ obtained from the primary optical density model (figure 1, 2). The basic functions for differentiation are smooth models describing the dependence of density D on t and T. Thus, the "two-step" process of building a model was used:

Stage I: smoothing, using the neural network approach, the initial data obtained in a series of experiments to determine the optical density.

Stage II: the use of the obtained model dependence for the construction of an estimate of the partial derivative with respect to time: $\frac{\partial D}{\partial t}$.

The use of the second approach allows us to obtain a more informative model that preserves qualitative descriptive characteristics and smoothness (figure 5, 6).

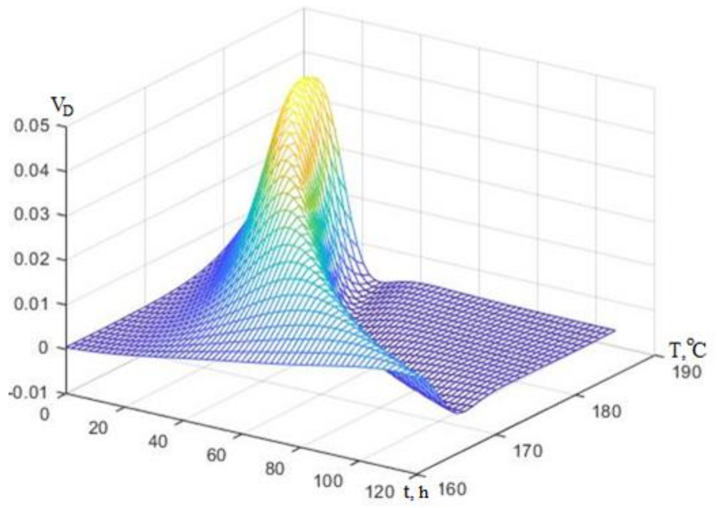

Figure 5. Dependence of the rate of change of optical density on the time and temperature test mineral engine oil Toyota Castle 10W-30 SL, built using the second approach.

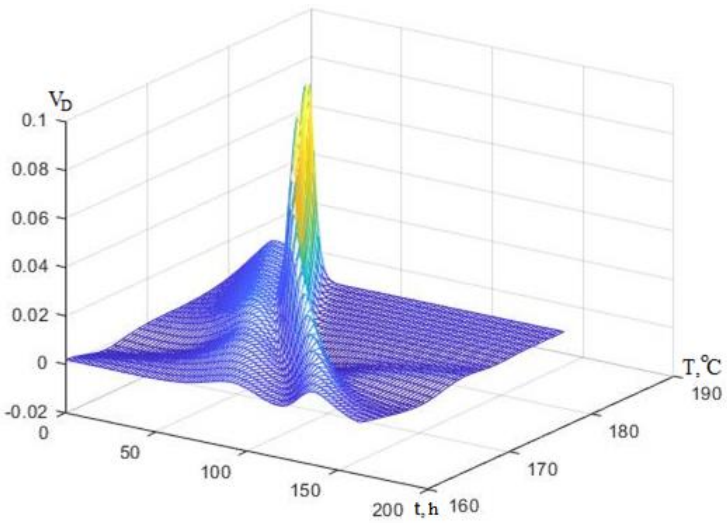

Figure 6. The dependence of the rate of change of optical density on the time and temperature of testing partially-synthetic engine oil Mannol Molibden 10W-40, built using the second approach.

Analyzing the obtained dependences, it can be noted that the "ridge" of peaks in the rate of change in optical density is located almost linearly in the "time – temperature" parameter plane in the first approach, and the second approach leads to a dependency that has a more complex non-linear character (figure 7, 8).

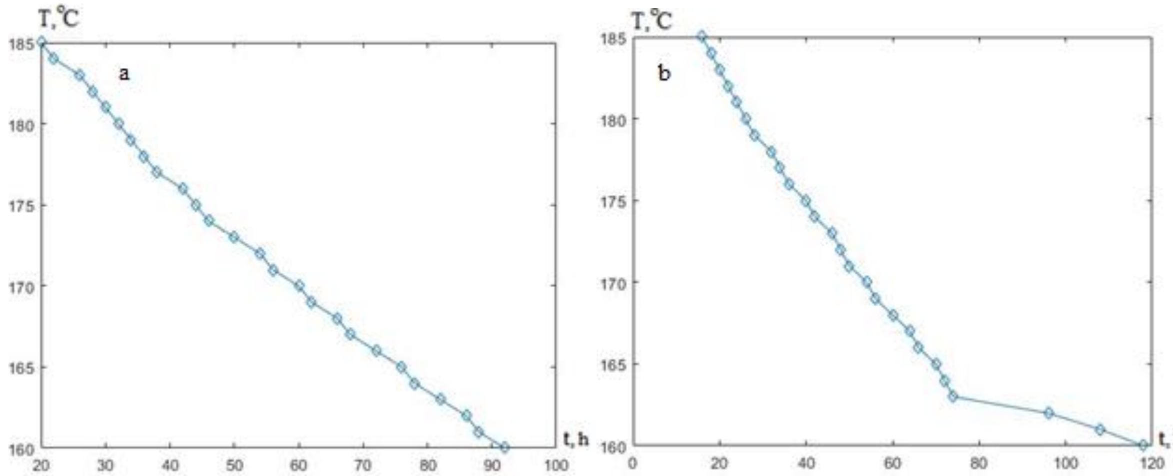

Figure 7. Temperature dependence of the peak of the rate of change of optical density from the time of testing mineral engine oil Toyota Castle 10W-30 SL, *a* built using the first approach, *b* built using the second approach.

Let us proceed to a discussion of the results obtained from the point of view of assumptions about the nature of the flow of thermal-oxidative processes and the suitability of the described approaches.

A comparison of the two approaches to modeling the marginal resource of lubricants shows that, despite the fact that the "two-step" modeling in the second approach leads to the imposition of errors in the construction of each model, this approach shows a more adequate result, allowing you to identify the characteristic qualitative patterns of achieving a critical resource oils under the influence of high temperatures.

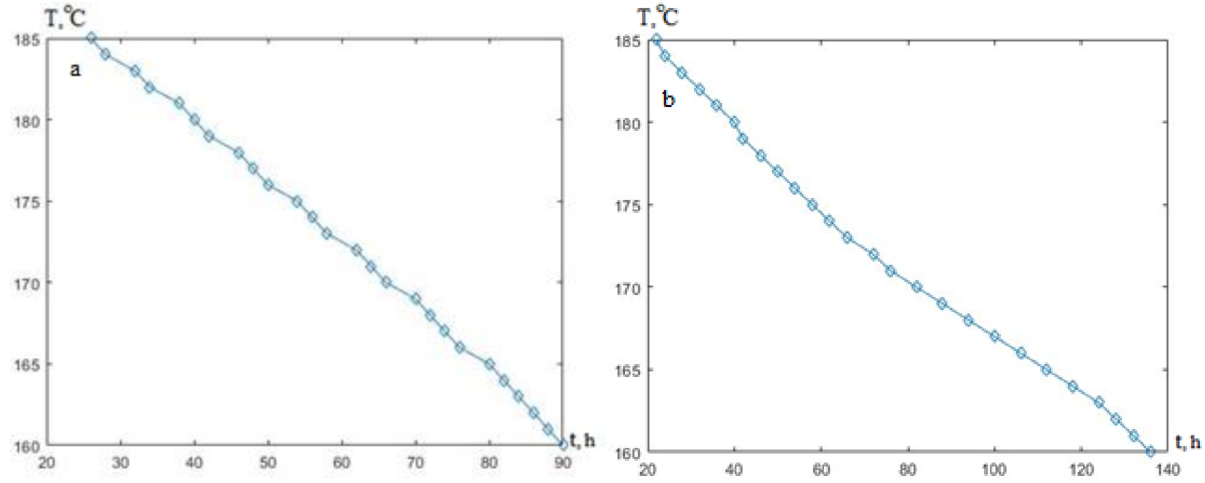

Figure 8. Temperature dependence of the peak of the rate of change of optical density from the time of testing part-synthetic Mannol Molibden 10W-40SL/CF motor oil, *a* built using the first approach, *b* built using the second approach.

Analysis of the simulation results using the first approach shows that the information content of the model in terms of describing the qualitative regularities of the process of thermo-oxidative degradation is inferior to the similar characteristics for models built in accordance with the second approach.

Conducted experimental studies found:

In conclusion, we note that the adequacy of building models from experimental data is determined by many factors. The model can have various purposes. Predictive models should have a high accuracy, determined by the selected quality criteria, for example, standard deviation, etc. as was presented in [8]. Research (cognitive) models have a different purpose and are used for a deeper study of the processes taking place. Here, a more important role is played by the ability of the model to describe the qualitative characteristics of the process.

In this work, emphasis was placed on the ability of the model to contribute to the mapping of the regularities of the course of the process of thermo-oxidative destruction for its deeper study. The second approach for our needs turned out to be more informative.

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