Determination of statistical data of conditional probabilities of the technical condition of internal combustion engines when compiling the Bayes diagnostic table

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Abstract. One of attractive methods for in-place diagnostics of internal combustion engines is the method based on using the generalized Bayes formula of conditional probabilities. The article is devoted to the applicability improvement of the Bayes algorithm for assessing the technical condition of internal combustion engines. The use of this algorithm involves the compilation of a diagnostic table, the elements of which are conditional probabilities of selected diagnoses in case of a range of faults. Their relevant determination requires a large amount of statistical data, which is often lacking. To supplement deficient data and increase the reliability of obtained results, the authors propose to use a method for simulating patterns of changes in design parameters of the technical condition of internal combustion engines depending on operating time.

1. Introduction

Based on the accepted algorithm of the Bayes method, one can compile a diagnostic table, the elements of which are conditional probabilities of accepted diagnoses in case of a range of faults [1, 2]. These probabilities are generated on the basis of statistical data on maintenance and repair of internal combustion engines. Often, however, information about the technical condition of the engine, depending on its design parameters and operating time, is not enough or is contradictory. This is also caused by the currently common aggregate method for extending the operational life of an internal combustion engine. It results in a problem of a lack of relevant statistical information, which requires additional research. One of the solutions to the problem of determining the missing information for the Bayes diagnostic matrix is a numerical simulation of the influence of the operating time of an internal combustion engine on the intensity of changes in parameters of its technical conditions [3].
2. Methods

When determining the diagnosis of the technical condition of an internal combustion engine using the Bayes method, it is necessary to compile a diagnostic table (matrix), the elements of which are generated on the basis of previously collected statistical data. The diagnostic table contains conditional probabilities of digit orders of a set of signs for various technical conditions of the engine (diagnoses). Wherein, dimensions of the table are determined by the number of selected probable manifestations of signs of failures and fault conditions [4].

The diagnostic table includes only a priori probabilities of selected diagnoses. At the same time, it is important to provide for the possibility of refining and changing the table in the process of diagnostics, for which not only the probability values but also the following values are fixed:

- $N$ – the total number of diagnostic objects used to compile the diagnostic matrix;
- $N_i$ – the number of objects with the diagnosis $D$;
- $N_{ij}$ – the number of objects with the diagnosis $D$ examined in regards to $k_j$.

To obtain diagnostic results with a high probability of reliability, it is necessary to continuously record the technical condition of the engine during each case of routine maintenance with the registration of the condition of its systems and mechanisms, when compiling this matrix. According to the results of practical diagnostic studies, satisfactory convergence of results appears when the sample size is greater than 200. One of the issues that cause difficulties when compiling the Bayes diagnostic table is the fact that, according to the regulatory and technical documentation, not all the necessary information on the technical condition of engine components is recorded during these works.

Let us consider an example of compiling a diagnostic table according to the Bayes algorithm for the D-243 engine [5].

Experience in operating internal combustion engines and the content of papers in accordance with the regulatory and technical documents on their maintenance show that the current condition of the engine is primarily determined by the condition of the air supply system (ASS), fuel supply system (FSS), and cylinder-piston group (CPG) [6].

As a diagnosis, four main engine conditions are chosen:
- faults in the air supply system (ASS);
- faults in the fuel supply system (FSS);
- faults in the cylinder-piston group (CPG);
- engine in good condition.

3. Results

The correct choice of diagnostic parameters (signs) is quite a crucial point, as it affects not only the reliability of the diagnosis and the number of experiments to get it but also reduces the probability of errors of the first and second kind. Considering the internal combustion engine as a dynamic object with stationary characteristics, one can use identification methods for such objects. They reflect the dynamic characteristics of the system and depend on its technical condition. As a diagnostic sign, let’s one can choose the intensity of change in engine performance after a single change in the regulator adjustment lever position – transient functions:

- rotation speed change intensity $T_{n1}(k1i)$;
- fuel supply change intensity $T_{g1}(k2i)$;
- air flow change intensity $T_{a1}(k3i)$.

Each sign has three condition levels: good, satisfactory and bad, corresponding to system faults:
- good change intensity $k_{j1}$;
- satisfactory change intensity $k_{j2}$;
- bad change intensity $k_{j3}$.

Determination of the range of change of indicators from good to bad values requires information on the correspondence of these data for engines with zero and maximum operating time [7]. These characteristics are determined by regulatory and technical documents or they can be obtained during bench testing of engines with different technical conditions, and serve to determine boundary conditions when conducting the diagnostics.
Baseline data for the engine being diagnosed are also:
- overhaul life;
- maintenance rate;
- current operating time.

A Bayes diagnostic table on engine failures and faults at selected diagnostic parameters is given in Table 1 below [8].

**Table 1. Bayes diagnostic table.**

| Engine condition $D_i$ | Signs $k_j$ | $k_{i1}$ | $k_{i2}$ | $k_{i3}$ | $k_{j1}$ | $k_{j2}$ | $k_{j3}$ | $P(D_i)$ |
|------------------------|-------------|---------|---------|---------|---------|---------|---------|---------|
| F       | Rotation speed $k_1$ | Fuel consumption $k_2$ | Air flow $k_3$ |
| Faults of the ASS $D_1$ | $P(k_{1i}/D_1)$ | $P(k_{2i}/D_1)$ | $P(k_{3i}/D_1)$ | $P(D_1)$ |
| Faults of the FSS $D_2$ | $P(k_{1i}/D_2)$ | $P(k_{2i}/D_2)$ | $P(k_{3i}/D_2)$ | $P(D_2)$ |
| Faults of the CPG $D_3$ | $P(k_{1i}/D_3)$ | $P(k_{2i}/D_3)$ | $P(k_{3i}/D_3)$ | $P(D_3)$ |
| Good condition $D_4$ | $P(k_{1i}/D_4)$ | $P(k_{2i}/D_4)$ | $P(k_{3i}/D_4)$ | $P(D_4)$ |

where $P(D_i)$ – a priori probability of the hypotheses $D_i$;
$P(k_i/D_i)$ – probability of the hypotheses $k_i$ upon the occurrence of the event $D_i$(a posteriori probability).

These values are related by the Bayes formula.

It is necessary to determine the probability of the engine condition diagnosis $D_i$, if there is one of the possible joint manifestations of signs $k_{i1}$, $k_{i2}$, and $k_{i3}$.

According to the requirements of regulatory and technical documents, the service life of an internal combustion engine is determined by the service life of its basic parts, which are the cylinder block and the crankshaft. It is usually considered that the reason for the engine overhaul is the extremely worn condition of the cylinder block or crankshaft.

According to studies [9], the operational performance of the engine in normal operating conditions is reduced according to the law of smooth continuous function with different intensities (Figure 1).

**Figure 1.** Dependence of compression $k$ on the D-243 engine operating time $l$

Note: 1 – experimental data, 2 – approximated data.
The parameters of this function are determined by operating modes of the engine, the quality of maintenance works carried out and the consumables used. This pattern of change in the effective indicators of engine operation is the result of a violation of adjustments, pollution of fuel and air supply elements, as well as the inevitable occurrence of changes in design parameters of the technical condition (Figure 2) [10].

Taking into account the probabilistic nature of patterns of change in design parameters of the technical condition and the normal distribution law of random variables, one can assume that the probability of good condition of the CPG when the compression changes from \( K_{\text{min}} \) to \( K_{\text{max}} \) changes exponentially [11, 12], as shown in Figure 3.

Then the law of change in the probability of good condition of the engine \( P(D_s) \) has the form shown in Figure 4.
The probability of the CPG good condition, depending on the compression and operating time

The proposed methods for modeling probabilities allows simplifying the procedure of using the Bayes algorithm for in-place diagnostics of internal combustion engines and can be applied in the practical implementation of this algorithm.

The significance of the regression model is verified using the Fisher F-criterion, the calculated value of which is determined as the ratio of the variance of initial series of observation of the studied indicator and the unbiased estimate of the variance of residual sequence for this model (Table 2).

Table 2. Fisher criteria for regression equations.

| The parameter being determined | Parameter level | Regression equation | Regression coefficient | F  | F_table |
|--------------------------------|----------------|---------------------|------------------------|----|--------|
|                               | P_a=2 kPa      | n = a e^bPa         | 7.0776                 | 0.2361 | 17.81  | 5.32 |
|                               | P_a=4 kPa      | n = a e^bPa         | 7.0231                 | 0.2519 | 27.83  | 5.32 |
|                               | P_a=7 kPa      | n = a e^bPa         | 6.9599                 | 0.2764 | 50.95  | 5.32 |
|                               | P_f=18.5 MPa   | n = a e^b_Pf        | 7.079                  | 0.2346 | 16.14  | 5.32 |
|                               | P_f=16.5 MPa   | n = a e^b_Pf        | 7.0132                 | 0.2589 | 27.61  | 5.32 |
|                               | P_f=15.5 MPa   | n = a e^b_Pf        | 6.962                  | 0.273  | 47.9   | 5.32 |
|                               | k=2.7 MPa      | n = a e^b_k          | 7.0273                 | 0.2523 | 25.28  | 5.32 |
|                               | k=2.4 MPa      | n = a e^b_k          | 6.9536                 | 0.2798 | 37.2   | 5.32 |
|                               | k=2.1 MPa      | n = a e^b_k          | 6.9129                 | 0.2888 | 59.72  | 5.32 |

According to the Fisher distribution tables, the table value of the Fisher criterion for a given level of significance is determined taking into account that the number of degrees of freedom for the total sum of squares (large variance) is 1, and the number of degrees of freedom for the residual sum of squares (smaller dispersion) with linear regression is n-2. The table value of the Fisher criterion is the maximum possible value of the criterion for these degrees of freedom and the level of significance α under the influence of random factors. The significance level α is the probability of rejecting the correct hypothesis, if it is true. Accept α equal to 0.05.

Since, in this case, the actual value of F > F_table, the determination coefficient is statistically significant, which means that the estimated value of the regression equation is statistically reliable.
4. Conclusion
The analysis shows that the proposed method for determining the statistical data of conditional probabilities of the technical condition provides relevant results.

5. References
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