Synthesis of Control Systems for Complex Technical Objects

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Abstract. The paper considers the task of improving the reliability of standby diesel generator sets of nuclear power plants (NPP) of the Russian Federation. A solution to the problem using a portable software and hardware diagnostic complex (I&C complex) that provides registration, processing, analysis and storage of data is proposed. The article describes in detail the main provisions of the methodology to monitor the state of the object. A method of analyzing the state of a diesel generator unit (DGU) based on representing an array of vibration and ultrasound parameters in the space of the principal components is used. The results of I&C complex tests for the diagnostics of NPP DGU are presented. An assessment of the resource of equipment based on the results of diagnostics for risk management, improving equipment reliability and cost savings is proposed.

1. Introduction
Multichannel diagnostic systems are used to monitor the state of complex dimensional objects, such as diesel engines, powerful compressors, pumps. Multichanneling is associated with the need to register information of one physical nature, for example, vibration, in various parts of an object, as recommended in various regulatory documents [1]. In the case of monitoring the diesel engine state, systems based on data recording of only one physical nature are inferior to systems that implement a set of methods. This paper illustrates the approach to the synthesis of a multichannel system using as an example designing a diagnosing set for diesel engines.

The diesel engine is used in railway and water transport, also as backup power sources, including potentially dangerous and harmful industries. The engine can provide continuous operation for thousands of hours under normal operating conditions. However, in the event of a defect, its growth can be quite fast and lead to serious failures, death of people, property and environmental damage. One of the most frequent defects is the malfunction of the fuel injection system, which causes about 43% of engine failures [2]. Other important elements are cylinder heads and valves; their defects make up a high percentage of engine failures (19%). Bearing defects also contribute significantly.

The synthesis of the diesel diagnostic system, improvement, the choice of one or another implementation can be based on the analysis of desirable properties that characterize the ability to assess the technical state [3]. Among the requirements for diagnostic systems are:

1) identifiability, by which it is accepted to understand the ability to decide, taking into account the current process conditions, whether the object is functioning normally, and, if it is functioning abnormally, to see if its source is a known malfunction or an unknown, new malfunction;
2) isolability is the ability of the diagnostic system to distinguish between different failures; in ideal conditions free of noise and uncertainties, this means that an unambiguous diagnosis is formulated at the system output, eliminating false information about missing defects;
3) speed of detection;
4) robustness;
5) the ability to assess diagnostic errors in order to predict the levels of confidence in the diagnostic decisions of the system;
6) adaptability to the operating conditions of the technological process and the environment;
7) the ability to explain the root causes of occurrence and consequences of the flaw growth, etc.

The first two of the above seven requirements should be recognized as the most important. The methods taken as the basis of the developed system should ensure identifiability and isolability. The following approaches are widely used in the diesel engine diagnosis: vibration monitoring [4-6], waste oil analysis [7], indicator pressure monitoring in the cylinder [8], flywheel instantaneous angular rate control [9], ultrasonic control [10,11], temperature control [12], exhaust gas monitoring [13].

The known methods [1-12] generally meet the requirement of identifiability. However, only vibrational, ultrasonic, temperature methods and a method for measuring pressure in cylinders meet the requirement of isolability due to the localization of defects in a particular assembly unit.

The vibration monitoring has become widespread due to its sensitivity to most defects. However, this method has remained rather limited when applied to diesel engines, mainly due to the complexity of vibration signals that are generated by various sources and the corresponding transmission paths from the sources to the location of the recording.

The ultrasonic (sound) method has advantages over the vibration approach - greater sensitivity to local processes, detuning from the influence of processes in assembly units adjacent to the controlled one. These advantages make it possible to localize defects in bearings [10] and cylinders [11]. The method is not widely used as the signals are weaker than the vibration signals and quickly decay when moving away from the source.

Carrying out temperature control of the diesel engine allows timely to identify defects in the fuel injection equipment components. Monitoring the temperature state of the diesel engine framework and its main units allows to identify places with a strongly pronounced change in the temperature field that in some cases permits to localize bearing defects.

The pressure in the cylinder as a crankshaft (CS) rotation angle and the compression strokes in the engine cycle is used to obtain quantitative information about the fuel injection equipment and the state of the cylinder-piston groups (CPG) [8]. However, methods for measuring pressure in the cylinders are not always suitable for use in engines in operation because they are expensive, their maintenance or calibration are heavy.

Thus, each of these four methods is sensitive to one defect and insensitive to the others; measuring systems synthesis based on recording data of only one physical nature does not provide reliable control of objects. There is a reason to believe that the Atlant type vibration systems with eight and sixteen recording channels should be inferior to systems that, in addition to processing vibration signals, take temperature, pressure in the cylinder and other characteristics into account.

There is a need for formalization of approaches in the assessment of diagnostic systems in terms of compliance with basic and additional requirements. This work is aimed at developing methods for selecting the quantity and quality of measuring channels.

2. Transformation of measurements in the diagnostic system
It is advisable to describe the various transformations through which process measurements pass before a final diagnostic conclusion is made at the design stage of diagnostic systems [14].
Figure 1 shows the various transformations that data undergoes during diagnosis. The measurement space is the input data $x_1, x_2, ..., x_N$ for the diagnostic system. A feature space is a space of vectors $y(y_1, ..., y_i)$, where the $y_i$-th feature obtained as a function of measurements using a priori knowledge of the problem. Here, measurements are analyzed and combined using a priori knowledge of the process to extract the process characteristics that are most significant from the point of view of diagnosing. The mapping from the feature space to the decision space must satisfy some target function (for example, minimizing incorrect classification). This transformation is achieved either by using the discriminant function, or in some cases by using simple threshold functions. The decision space is the point $d=[d_1, ..., d_k]$, where $k$ is the number of decision variables obtained by the corresponding transformations of the feature space. Class space is a set of integers $c=[c_1, ..., c_M]$, where $m$ is the number of defect classes indexing the failure classes, indicating to which failure class (or classes), including the normal region, this measurement result belongs. Thus, the class space is the final interpretation of the diagnostic system supplied to the user. Conversions from the decision space to the class space are again performed using threshold functions, pattern matching, or symbolic reasoning, depending on the situation.

There are two ways to develop the feature space from the measurement space, namely: selecting features and extracting features. When selecting an object, several important measurements of the original measurement space are simply selected. Feature extraction is a procedure of transforming the measurement space into a space of fewer dimensions. For example, when imaging diesel areas manually or automatically, the temperatures of the cylinder exhaust pipes are identified or the maximum compression pressure is determined from the indicator diagrams of the cylinders — these are examples of the feature selection. And the RMS calculation of the vibration and ultrasound signals is the case of feature extraction.

The advantage of converting the measurement space to the feature space is to simplify the subsequent classification. Studying the design and functioning of the process unit allows to develop an effective mapping from the measurement space into the feature space.

The transformation from the measurement into the feature space is performed through the use of prior knowledge of the object, while the conversion from the feature space to the decision space is implemented as a search or training algorithm. The formation of a powerful feature space can significantly reduce the load on the search / learning algorithm.

The decision space is usually mapped to the class space using simple threshold functions. The decision space and class space in most cases have the same measurement. However, it would be preferable to maintain separate decision and class spaces, because in some cases it is not possible to force the diagnostic classifier to offer clear decisions.

Thus, the effectiveness of the diagnostic system is determined by the choice of diagnostic features, i.e. a representation of the relation between the state and its manifestations in the sensor signals.

It is proposed to use the deviation model [15] to represent the feature space. Deviations are understood as discrepancies between the actual values of the features and those values that should be observed in the normal object operation. The sensor response to a defect, expressed as a deviation, can be used to construct a feature space. Deviations should be close to zero when there are no defects, but show “significant” values when there are changes in the object. In real situations, residual values are not equal to zero due to measurement noise, technical process, model inaccuracies, errors in sensors, etc.

Building a feature space requires some form of redundancy. There are two types of redundancy, hardware redundancy and analytical redundancy. The first requires redundant sensors. On the other hand, analytical redundancy (also called functional, inherent, or artificial redundancy) is achieved.
from the functional relationship between process variables and is usually provided by a set of algebraic or temporal relations between the states, inputs and outputs of the system.

Additional degrees of freedom resulting from redundancy contribute to better identifiability and isolability.

It is assumed that there are sets of features, each of which is sensitive to one class of defects, while it is insensitive to other faults and unknown input signals. The main idea is that if there is a defect, all insensitive parameters show only small deviations, and the parameters that are sensitive to the defect will deviate significantly and lead to the appearance of large residuals. A unique failure signature ensures its reliable isolability. It is shown [16] that the best isolability can be achieved when the deviations take positive and negative values for various defects (for example, when the RMS of the ultrasonic signal increases and the temperature recorded simultaneously at the same point decreases).

Deviations taken into account in the system should also provide reliability in the sense that the solutions are not distorted by such unknown input data as unstructured uncertainties, process and measurement noise, and modeling uncertainties.

Either a model obtained analytically or a black box model obtained empirically can be implemented.

3. An empirical model of a diesel engine diagnostic system

Let the measurement space be represented by signals from $n$ sensors. This space is transformed into the $Y$ feature space, which is represented by deviations of the diagnostic parameters $\Delta y_1, \ldots, \Delta y_n$ as a result of defects. The $Y$ space, providing identification of $m$ state classes in general, can be described by the model:

$$
Y = \begin{pmatrix}
\Delta y_1^1 & \cdots & \Delta y_1^n \\
\vdots & \ddots & \vdots \\
\Delta y_m^1 & \cdots & \Delta y_m^n
\end{pmatrix}
$$

(1)

This modeling concept can be illustrated by the development of a system that provides diagnostics for a four-cylinder diesel engine (a simple example is considered to illustrate the approach). Suppose that three groups of defects can occur in the engine: injector malfunction, deviation in the piston-cylinder group, and CS bearings malfunction. The engine state is evaluated by four methods: vibration at six points of the casing (see Figure 2) $x_{v1} - x_{v6}$, ultrasound in the bearing area $x_{u1} - x_{u4}$, temperature of the exhaust pipes of the cylinders $x_{t1} - x_{t4}$, and pressure in the cylinders $x_{p1} - x_{p4}$.

![Figure 2. Location of vibration control points on the engine diagram.](image)

The corresponding parameters are measured and converted into diagnostic features: $y_{v1}, y_{v6}, y_{u4}, y_{t1}, y_{t4}, y_{p1}, y_{p4}$ — deviations of the RMS signals of vibration and ultrasound, maximum temperatures and pressures from nominal values in the normal operation of the object. Table 1 shows the mapping of 18-dimensional feature vectors into 12 classes of states: nozzle failure 1-4 (No. of defects 1-4), deviations in the CPG operation 1-4 (No. of defects 5-8), SC bearing defect 1-4 (No. of defects 9-12).

Zero means that the sensor is not affected by changes in the state and recording more or less than zero means that the sensor is more or less sensitive to the corresponding state of the system.
Table 1. Model of the diesel engine diagnostic system.

| No of defect | Parameter deviation |
|--------------|---------------------|
|              | $y_{v1}$ | $y_{v2}$ | $y_{v3}$ | $y_{v4}$ | $y_{v5}$ | $y_{v6}$ | $y_{t1}$ | $y_{t2}$ | $y_{t3}$ | $y_{t4}$ | $y_{u1}$ | $y_{u2}$ | $y_{u3}$ | $y_{u4}$ | $y_{p1}$ | $y_{p2}$ | $y_{p3}$ | $y_{p4}$ |
| 1            | 0.3      | 0.2      | 0.1      | 0.3      | 0.2      | 0.1      | -0.1     | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      |
| 2            | 0.3      | 0.2      | 0.1      | 0.3      | 0.2      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      |
| 3            | 0.1      | 0.2      | 0.1      | 0.3      | 0.2      | 0.1      | -0.1     | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      |
| 4            | 0.4      | 0.3      | 0.2      | 0.3      | 0.2      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      |
| 5            | 0.4      | 0.3      | 0.2      | 0.3      | 0.2      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      |
| 6            | 0.3      | 0.4      | 0.3      | 0.2      | 0.3      | 0.2      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      |
| 7            | 0.2      | 0.3      | 0.2      | 0.3      | 0.2      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      |
| 8            | 0.1      | 0.2      | 0.1      | 0.3      | 0.2      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      |
| 9            | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      |
| 10           | 0.1      | 0.2      | 0.1      | 0.2      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      |
| 11           | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      |
| 12           | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      | 0.1      |

The table is compiled on the basis of monitoring the parameters behavior in real diesel engines [1-3, 7, 9-11]. The system model takes into account:

1) the average sensitivity of vibration indicators to defects in nozzles and CPG;
2) low sensitivity of vibration indicators to defects of bearings;
3) the influence of defects on vibration sensors installed both near a faulty part and in other areas;
4) in general, an increase in vibration indicators if there is any defect;
5) the average sensitivity of temperature parameters to defects in the CPG;
6) low sensitivity of temperature parameters to defects in nozzles and bearings;
7) a decrease in the temperature of faulty CPG and nozzles and a simultaneous increase in the temperature of serviceable nozzles and cylinders;
8) low sensitivity of ultrasound parameters to defects in the CPG and nozzles;
9) high sensitivity of ultrasonic parameters to defects in nozzles and bearings;
10) the influence of defects on ultrasonic sensors installed near a faulty part is greater than on sensors in other areas;
11) in general, an increase in ultrasound indicators if there is any defect;
12) high sensitivity of pressure parameters to defects in nozzles and CPG;
13) the lack of pressure parameter sensitivity to bearing defects, a decrease in the temperature of faulty CPGs and nozzles, and a simultaneous increase in the temperature of serviceable nozzles and cylinders;
14) a pressure decrease in faulty CPG and nozzles and a simultaneous pressure increase in serviceable nozzles and cylinders.

But the model does not take into account:
1) the influence of the driven mechanism - the generator or pump unit;
2) the influence of the engine operating mode (it is believed that during diagnosis the diesel engine runs at rated power);
3) the degree of defect development,
4) the influence of external factors;
5) noise and measurement uncertainty;
6) the presence of more than one defect.

As can be seen from table 1, each fault is characterized by a unique set of parameters. Each row of table 1 can be considered as the coordinates of a vector in the feature space, its position (with some tolerance) can be considered as a decision on belonging to one of the classes. The distance between the vector and its closest “neighbor” can be considered as a measure of isolability with respect to these two defects. The distance between two points in the n-dimensional space \( d_{ij} \) can be calculated by the formula:

\[
    d_{ij} = \sqrt{\sum_{k=1}^{12} (\Delta y_k^i - \Delta y_k^j)^2}
\]  

(2)

where \( \Delta y_k^i \) и \( \Delta y_k^j \) are the coordinates of neighboring vectors.

The vector-to-the zero coordinate distance shows the identifiability that the system can provide when diagnosing one of the defects. The distance from the origin to the point in n-dimensional space \( d_{0i} \) can be calculated by the formula:

\[
    d_{0i} = \sqrt{\sum_{k=1}^{12} (\Delta y_k^i)^2}
\]  

(3)

where \( i \) is the vector number. The model demonstrates that the identifiability of some defects is less than that of others, and also that some vectors have close coordinates, i.e. relatively low isolability.

We will evaluate the identifiability by the length of the shortest vector (corresponding to the most complex identifiable defect) \( d_{0\text{min}} \), and the isolability by the distance between the two closest \( d_{\text{min}} \) vectors.

Theoretically, the system can provide identifiability and isolability only on the basis of the results of measuring vibration or ultrasound. In a real system, under the influence of factors that the model does not take into account, the vector coordinates can shift so that the system cannot ensure the correct mapping of the feature space into the decision space. The hardware and functional redundancy of the diagnostic system is aimed at ensuring resistance to various external interferences, adaptability to conditions. There arises the question of the quantitative justification of the measuring channels redundancy from the point of view of their influence on the achieved identification, isolability of the diagnostic system and its other characteristics.

4. Synthesis of the diagnostic system measuring channels
The achieved identifiability when using various channels of the simulated diagnostic system is calculated according to formula 2. The letters \( v, u, t, p \) denote the channels for recording vibration, ultrasound, temperature, and pressure. Table 2 discusses system options with only one type of primary transducers - vibration and ultrasound - as well as various combinations of measuring channels that provide two, three and all four types of measurements. The channels for recording temperature and pressure are not considered separately, since it is obvious from Table 1 that they cannot ensure the identifiability of all states in the diagnostic system by themselves. After calculating the identifiability of all states, we chose the least values (last line).

We consider the systems with the indicator not lower than 50% as systems providing acceptable identifiability. Options No. 1-4, 7 and 8 require further development. The prototypes of system No. 7 can be “Admiral” and “Magistral” complexes, based on record-keeping and processing pressure and
temperature indicators. These systems are good tools for tuning and diagnosing defects in nozzles and CPGs, but they do not permit to identify bearing defects, although this group of defects often leads to equipment failures.

Table 2. Identifiability when using various channels of the diagnostic system

| The involved measuring channels | Identifiability |
|---------------------------------|-----------------|
|                                 | v   | u   | u+p | v+t | v+u | u+p | u+t | t+p | v+u | u+p | v+t | +u | +p |
| identifiable state              | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | 10  | 11  | 12 |
| nozzle1 failure                 | 0.44| 0.1 | 1.02| 0.47| 0.45| 0.93| 0.2 | 1.03| 1.02| 0.94| 0.48| 1.04|
| nozzle2 failure                 | 0.56| 0.14| 1.01| 0.59| 0.57| 0.86| 0.24| 1.03| 1.02| 0.88| 0.61| 1.04|
| nozzle3 failure                 | 0.56| 0.17| 0.94| 0.59| 0.58| 0.77| 0.26| 0.96| 0.95| 0.8 | 0.62| 0.97|
| nozzle 4 failure                | 0.44| 0.2 | 0.77| 0.47| 0.48| 0.66| 0.26| 0.79| 0.79| 0.69| 0.51| 0.81|
| CPG 1 malfunction               | 0.66| 0.26| 1.13| 0.75| 0.71| 0.96| 0.46| 1.19| 1.16| 1.03| 0.8 | 1.22|
| CPG 2 malfunction               | 0.79| 0.22| 1.16| 0.9 | 0.82| 0.88| 0.48| 1.24| 1.18| 0.97| 0.93| 1.26|
| CPG 3 malfunction               | 0.79| 0.22| 1.1 | 0.9 | 0.82| 0.79| 0.48| 1.17| 1.12| 0.89| 0.93| 1.2 |
| CPG 4 malfunction               | 0.66| 0.2 | 0.91| 0.75| 0.69| 0.66| 0.42| 0.98| 0.93| 0.76| 0.78| 1  |
| CS bearing 1 defect             | 0.24| 0.92| 0.24| 0.24| 0.95| 0.92| 0.92| 0.24| 0.95| 0.92| 0.95| 0.95|
| CS bearing 2 defect             | 0.33| 0.85| 0.33| 0.33| 0.91| 0.85| 0.85| 0.33| 0.91| 0.85| 0.91| 0.91|
| CS bearing 3 defect             | 0.33| 0.75| 0.33| 0.33| 0.82| 0.75| 0.75| 0.33| 0.82| 0.75| 0.82| 0.82|
| CS bearing 4 defect             | 0.24| 0.63| 0.24| 0.24| 0.68| 0.63| 0.63| 0.24| 0.68| 0.63| 0.68| 0.68|
| The least $d_{0i}$              | 0.24| 0.1 | 0.24| 0.24| 0.45| 0.63| 0.2 | 0.24| 0.68| 0.63| 0.48| 0.68|

$$\sum_{j=1}^{M} d_{0j} = \begin{array}{cccccccccccc}
6.04 & 4.66 & 9.18 & 6.56 & 8.48 & 9.66 & 5.95 & 9.53 & 11.53 & 10.11 & 9.02 & 11.9 \\
\end{array}$$

Identification analysis indicates close values of these indicators in four systems (No. 6, 9, 10, 12). To choose between 14- and 18-channel systems, we make a comparison upon isolability indicators. To do this, we calculate the isolability of each pair of states, achieved during the operation of various systems, according to formula 3. The results of systems 9 and 12 analysis are presented in Tables 3 and 4.

According to the data in Table 3, the separation of nozzle defects causes the greatest difficulty: states No. 1–4 have close coordinates in the state space. Another problem is the difference in defects of nozzles and cylinders (pairs 1 and 5, 2 and 6).

The data in Table 4 show that the introduction of additional temperature channels significantly increases the probability of nozzle defects separation, but the difference in states 1 and 5, 2 and 6 remains a problem, despite the use of all eighteen measuring channels. Both systems due to ultrasonic channels provide identification and localization of bearing defects.

It should be noted that systems rejected by the identifiability parameter are also inferior in terms of isolability. So, this indicator for defects No. 1–4 does not exceed 0.2 in the system with only ultrasonic channels.
Table 3. Isolability of states in a system containing a channel for measuring ultrasound, pressure and vibration

| Isolated states | 1    | 2    | 3    | 4    | 5    | 6    | 7    | 8    | 9    | 10   | 11   | 12   |
|-----------------|------|------|------|------|------|------|------|------|------|------|------|------|
| 1               | -    | 0.37 | 0.48 | 0.46 | 0.4  | 0.7  | 0.7  | 0.6  | 0.8  | 0.8  | 0.8  | 0.8  |
| 2               | 0.37 | -    | 0.36 | 0.48 | 0.4  | 0.3  | 0.6  | 0.6  | 0.9  | 0.8  | 0.8  | 0.8  |
| 3               | 0.48 | 0.36 | -    | 0.37 | 0.3  | 0.6  | 0.4  | 0.5  | 0.9  | 0.8  | 0.7  | 0.7  |
| 4               | 0.46 | 0.48 | 0.37 | -    | 0.5  | 0.7  | 0.6  | 0.3  | 0.9  | 0.8  | 0.7  | 0.6  |
| 5               | 0.39 | 0.56 | 0.58 | 0.58 | -    | 0.7  | 0.7  | 0.6  | 0.9  | 0.9  | 0.9  | 0.9  |
| 6               | 0.71 | 0.39 | 0.63 | 0.73 | 0.7  | -    | 0.8  | 0.7  | 1.2  | 0.9  | 1.0  | 1    |
| 7               | 0.75 | 0.66 | 0.4  | 0.69 | 0.7  | 0.8  | -    | 0.7  | 1.2  | 1.1  | 0.8  | 0.9  |
| 8               | 0.62 | 0.62 | 0.59 | 0.39 | 0.6  | 0.7  | 0.7  | -    | 1.1  | 1.0  | 0.9  | 0.7  |
| 9               | 0.89 | 0.94 | 0.97 | 0.95 | 0.9  | 1.2  | 1.2  | 1.1  | -    | 0.9  | 1.2  | 1.1  |
| 10              | 0.89 | 0.84 | 0.84 | 0.84 | 0.9  | 0.9  | 1.1  | 1.0  | 0.9  | -    | 0.8  | 1.0  |
| 11              | 0.88 | 0.87 | 0.76 | 0.71 | 0.9  | 1.0  | 0.8  | 0.9  | 1.2  | 0.8  | -    | 0.6  |
| 12              | 0.81 | 0.84 | 0.79 | 0.63 | 0.9  | 1    | 0.9  | 0.7  | 1.1  | 1.0  | 0.6  | -    |

The least $d_{ij}$

Table 4. Isolability of states in the system containing the channel for measuring ultrasound, pressure, vibration, and temperature

| Isolated states | 1    | 2    | 3    | 4    | 5    | 6    | 7    | 8    | 9    | 10   | 11   | 12   |
|-----------------|------|------|------|------|------|------|------|------|------|------|------|------|
| 1               | -    | 1.5  | 1.2  | 1.2  | 0.3  | 1.6  | 1.3  | 1.2  | 1.2  | 1.2  | 1.2  | 1.2  |
| 2               | 1.5  | -    | 1.4  | 1.1  | 1.6  | 0.3  | 1.5  | 1.1  | 1.2  | 1.1  | 1.2  | 1.2  |
| 3               | 1.2  | 1.4  | -    | 1.2  | 1.3  | 1.5  | 0.4  | 1.3  | 1.2  | 1.1  | 1.0  | 1.0  |
| 4               | 1.2  | 1.1  | 1.2  | -    | 1.2  | 1.2  | 1.4  | 0.3  | 1.1  | 1.0  | 0.9  | 0.8  |
| 5               | 0.3  | 1.6  | 1.3  | 1.2  | -    | 1.6  | 1.3  | 1.3  | 1.3  | 1.2  | 1.2  | 1.2  |
| 6               | 1.6  | 0.3  | 1.5  | 1.2  | 1.6  | -    | 1.5  | 1.2  | 1.4  | 1.2  | 1.3  | 1.3  |
| 7               | 1.3  | 1.5  | 0.4  | 1.4  | 1.3  | 1.5  | -    | 1.4  | 1.4  | 1.3  | 1.1  | 1.2  |
| 8               | 1.2  | 1.1  | 1.3  | 0.3  | 1.3  | 1.2  | 1.4  | -    | 1.3  | 1.2  | 1.1  | 0.9  |
| 9               | 1.2  | 1.2  | 1.2  | 1.1  | 1.3  | 1.4  | 1.4  | 1.3  | -    | 0.9  | 1.2  | 1.1  |
| 10              | 1.2  | 1.1  | 1.1  | 1.0  | 1.3  | 1.2  | 1.3  | 1.2  | 0.9  | -    | 0.8  | 1.0  |
| 11              | 1.2  | 1.2  | 1.0  | 0.9  | 1.2  | 1.3  | 1.1  | 1.1  | 1.2  | 0.8  | -    | 0.6  |
| 12              | 1.2  | 1.2  | 1.0  | 0.8  | 1.2  | 1.3  | 1.2  | 0.9  | 1.1  | 1.0  | 0.6  | -    |

The least $d_{ij}$

Obviously, choosing the system with the largest number of recording channels ensures the best quality of diagnosis. Moreover, diagnostic systems with fewer channels can be used depending on the importance of a particular diagnosis object, the need for diagnosis.

The choice of a specific variant of the diagnostic system causes difficulties due to the multidimensionality of the task. The simulated diagnostic system operates with an 18-dimensional feature space, despite the fact that a simple diesel design and only three types of malfunctions are considered in this example. Approximation of the proposed approach to a real diagnostic situation would lead to a multiple increase in dimension. An approach which provides a decrease in dimensionality and visualization of diagnostic results is required when analyzing multidimensional data.

5. Comparison of diesel engine diagnostic systems
To assess the quality indicators of the diagnostic system, it is proposed to apply the principal component analyses (PCA) [17-19] to the data presented in Table 1. The PCA is based on the orthogonal decomposition of the covariance matrix of the system parameters in directions that explain the maximum data change. The main purpose of using the PCA is to find the factors that have a much smaller dimension than the original dataset, while correctly describing the main trends in the original
dataset. The possibility of reducing the dimension of the feature space is based on the fact that the information in the measuring channels is connected by correlation relations.

Let $p$ denote the number of system parameters; we consider the vector space as the $Y$-matrix $n \times p$, which covariance matrix is $\Sigma$. Lines in $Y$, $y_1$, $y_2$, . . . , $y_n$ are $p$-dimensional vectors corresponding to the samples; while columns are vectors of dimension $n$ of the corresponding variables. We can obtain the diagonal matrix $L$ from the matrix algebras $\Sigma$ with the help of the orthonormal matrix $U$, that is, $\Sigma=ULU^T$. Columns $U$, $u_1$, $u_2$, . . . , $u_p$, are usually called the principal components (PC) of the load vectors.

Diagonal elements $L_l$, $l_1$, $l_2$, . . . , $l_p$ are ordered eigenvalues $\Sigma$. They determine the variance value explained by each corresponding eigenvector. PC conversion is defined as follows:

$$T = YU \text{ or } \theta_i = Xu_i$$  \hspace{1cm} (4)

Equivalently, $Y$ is decomposed by PCA as $u^T$:

$$Y = TU^T = \sum_{i=1}^{p} \theta_i u_i^T$$  \hspace{1cm} (5)

The matrix $n \times p T=(\theta_1, \theta_2, \ldots, \theta_p)$ contains the so-called PC estimates, which are defined as the observed values of the PC for all $n$ observations. Given the fact that the covariance $T$ is a diagonal matrix, the vectors $\theta_i$ are uncorrelated.

Besides, the pairs $\theta_i$, $u_i$ are arranged in decreasing order in accordance with their eigenvalues $l_i$. In addition, it is rarely required to calculate all eigenvectors in practice, since most of the data variation can be represented by the first several ECs. If a smaller number $a<p$ is used, the decomposition becomes:

$$Y = \theta_1 u_1^T + \theta_2 u_2^T + \ldots + \theta_a u_a^T + E = \sum_{i=1}^{a} \theta_i u_i^T + E$$  \hspace{1cm} (6)

where $E$ is the remainder term. It is found that the first two or three ECs are often sufficient to explain the variability. Therefore, the dimension is significantly reduced.

By presenting the information from Table 1 in two-dimensional space, we can clearly demonstrate the system capabilities in identifying and isolating any of the 12 states. Substituting and removing individual columns, we can evaluate the contribution of individual measuring channels to ensure the quality of the system operation.

The feature spaces of four variants of diesel engine diagnostic systems are presented below (Figure 3). Images 3a, 3b, 3c and 3d are usually called load graphs, you can get the following information according to them:

1) on the better identifiability of some systems compared with others by a larger scatter of the vector coordinates;
2) on the identifiability of each of the states in the analyzed system by the vector positions relatively to zero;
3) on the isolability of each of the states in the analyzed system according to vector positions relatively to each other.

The first system is based on measuring vibration, temperature and ultrasound in various parts of the object. Judging by the vector positions of various states, the best identifiability and isolability are manifested by the system with bearing defects (No. 9-12). Comparing graph 3a with other load graphs, it should be noted that, in general, the points are scattered over a smaller area and this indicates less identifiability achieved when using the system in question compared to systems using a different combination of measuring channels. Indeed, the assessment of identifiability (Table 2) is 0.48, that does not correspond to a predetermined threshold of 0.5.

The system illustrated in graph 3b, is based on the interpretation of ultrasound, pressure and temperature. The system performance improvement achieved by replacing the vibration channels with
pressure measuring channels is obvious. The diagnosis quality improvement is manifested in a better identification of defects in the CPG and nozzles: the coordinates of the corresponding states (No. 1-8) on the graph are spaced from zero. The implementation and introduction of such a diagnostic system can provide reliable monitoring of the diesel engine state. During the operation of the analyzed system, it should be taken into account that the isolability achieved by identifying various states may differ. For example, the proximity of states No. 3 and No. 7 suggests that if the state “nozzle No. 3 failure” is detected, the “the CPG No. 3 malfunction” cannot be ruled out, while the remaining ten states are unlikely.

Further improvement is represented by the feature spaces of a system with channels for measuring ultrasound, pressure, vibration and a system in which, in addition to ultrasound, pressure, vibration, temperature is also measured.

**Figure 3.** The feature space representation in the eigenvector component coordinates of diagnostic systems with channels: a) vibration, temperature, ultrasound; b) ultrasound, pressure, temperature; c) ultrasound, pressure, vibration; d) ultrasound, pressure, vibration and temperature
The differences in graphs 3c and 3d are minor, but one can judge about the best isolability of pairs of states No. 3 and 7 and No. 6 and 2. Both graphs show the best identifiability with the widest scatter of vector coordinates. The proximity of states 9-12 to the zero coordinate does not indicate low identifiability of bearing defects (the data in Table 2 indicate the opposite), but it shows that in the systems under consideration, nozzle and CPG defects are better identified than bearing defects.

Thus, the load graphs are a visual representation of the information from Tables 2-4 and are a convenient tool at the system synthesis stage, permitting to pre-evaluate and adjust the properties of the designed diagnostic complex. Also, these graphs can help in analyzing the advantages and disadvantages of the existing systems.

6. Conclusions
The paper proposes an approach to the development of a diesel diagnostic system. By analyzing known diagnostic methods, those are selected which implementation as a part of the diagnostic system can ensure this system meeting the minimum requirements - identifiability and isolability. On considering the measurement conversion in the diagnostic system, we identify the most important stage - the mapping of the measurement space into the feature space. The presentation of state vectors in the feature space is proposed, the vector coordinates are deviations from the values of the properly functioning object parameters. An empirical model of the diesel diagnostic system is developed; it describes the deviations of the parameters of vibration, ultrasound, temperature and pressure under various states of the object. Identifiability and isolability values that characterize both the system that implements all types of control and systems that exclude some types of control are calculated. Calculation and analysis of isolability is performed for the systems with better identifiability.

Multidimensional feature spaces of various variants of diagnostic systems are projected into a two-dimensional space of principal components for visual clarity of the analysis.

The proposed approach to the analysis and synthesis of the diesel diagnostic system, including the development of the feature space model, the calculation of identifiability and isolability, can be used in the design of diagnostic complexes of various objects. To increase the accuracy of calculations, the feature space model can be improved taking into account the influence of a larger number of factors than in the present paper. At the design stage it is possible to consider system stability, adaptability and other characteristics in addition to assessing the compliance of the system with two minimum requirements.

The result of the work, besides the approach to the measuring channels synthesis, is several variants of a diesel engine diagnostic system, its development and implementation can provide reliable control of the technical state. A further increase in the number of measuring channels in these systems is unlikely to improve significantly their characteristics. The development of these systems should be ensured by the improvement of the feature space, namely the extraction of more sensitive features.

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