UDC 004.93

DATA-DRIVEN DIAGNOSTIC MODEL BUILDING FOR HELICOPTER GEAR HEALTH AND USAGE MONITORING

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ABSTRACT

Context. Modern technical objects (in particular vehicles) are extremely complex and place high demands on reliability. This requires automation of condition monitoring and fault diagnosis of objects and their components. The predictive maintenance improves operational readiness of technical objects. The object of study is a technical object health and usage monitoring process. The subject of study is a methods of computational intelligence for data-driven model building and related data processing tasks for health and usage monitoring system.

Objective. The purpose of the work is to formulate data processing problems, to form a data set for data-driven model building and construct simple method for automatic diagnostic model building on example of helicopter health and usage monitoring system.

Method. The method is proposed for the mapping of multidimensional data into a two-dimensional space preserving local properties of class separation, allowing for the visualization of multidimensional data and the production of simple diagnostic models for the automatic classification of diagnostic objects. The proposed method allows obtaining highly accurate diagnostic model with small training samples, provided that the frequency of classes in the samples is preserved. A method for synthesizing diagnostic models based on a two-layer feed-forward neural network is also proposed, which allows obtaining models in a non-iterative mode.

Results. A sample of observations of the state of helicopter gears was obtained, which can be used to compare data-driven diagnostic methods and data processing methods that solve the problems of data dimensionality reduction. The Software has been developed that allows displaying a sample from a multidimensional to a two-dimensional space, which makes it possible to visualize data and reduces the dimensionality of the data. Diagnostic models have been obtained that allow automating the decision-making process on whether the diagnosed object (helicopter gear) belongs to one of two classes of states.

Conclusions. The results of conducted experiments allow to conclude that the proposed method provides a significant reduction in the data dimensionality (in particular, for the considered problem of constructing a model for helicopter gear diagnosis, it reduces the data dimensionality due to the compression of features by 46876 times). As the results of the conducted experiments for randomly selected instances in a two-dimensional system of artificial features obtained on the basis of the proposed method showed a significant reduction of the sample for individual tasks may allow to provide acceptable accuracy. And taking into account individual estimates of the instance significance will allow, even for small samples, to ensure the topological representativeness of the formed sample in relation to the original sample.

The prospects for further research are to compare methods for constructing data-driven models, as well as methods for reducing the dimensionality of data based on the proposed sample. Additionally, it may be of interest to study a possible combination of the proposed method with methods for sample forming using metrics of the value of instances.

KEYWORDS: data-driven diagnosis, health and usage monitoring system, data dimensionality reduction, classification.

ABBREVIATIONS

DM is a diagnostic model;
HUMS is a Health and Usage Monitoring System;
MAE is a mean absolute error;
MSE is a mean squared error;
SSE is a sum squared error.

NOMENCLATURE

η is a neural network layer number;
$\psi^{(\eta,i)}$ is an activation function of i-th neuron of η-th layer;
$\varphi^{(\eta,i)}$ is a weight (postsynaptic) function of i-th neuron of η-th layer;
[ ] is a designation of a non-obligatory parameter;
< > is a designation of a tuple;
C is a center relative to which the distance is determined from the instances;
C^+ is a sample center;
C^{avg} is an average between class centers;
C^q is a q-th class center;
C^q_j is a value of j-th coordinate (feature) of the q-th class center;
$d(a, b)$ is a distance between points a and b;
E is a model error function;
f is a criterion (goal function);
$F()$ is a diagnostic (recognition) model structure;
F_i is an i-th model structure;
$f()$ is a user criterion characterizing the argument quality relatively to the problem being solved;
j is a feature number;
K is a number of classes;
M is a number of layers in neural network;
N is a number of input features;
N' is a number of features in a reduced set (subsample);
N_η is a number of neurons in the η-th layer of neural network;
opt is an optimal (desired or acceptable) value of the functional $f()$ for the problem being solved;
$P_{correct}$ is a correct decision making probability;
$P_{incorrect}$ is an incorrect decision making probability;
$P_{incorrect\ test}$ is a incorrect decision making probability for a test set;

DOI 10.15588/1607-3274-2025-1-11

$P_{\text{incorrect train}}$ is a incorrect decision making probability for a training set;

q is a class number;

S is a number of instances in the original sample;

s is an instance number;

S' is a number of precedents (examples) in a reduced sample (subsample);

S^q is a number of exemplars of a sample belonging to the q-th class;

S_{test} is a volume of a test set;

S_{train} is a volume of a training set;

w is a set of controlled (adjusted) parameters of a model;

w' is a set of controlled (adjusted) parameters of a reduced model;

$w_j^{(\eta,i)}$ is a value of j-th adjustable parameter (or weight) of j-th input of i-th node of η-th layer of a neural network;

$w^{(\eta,i)}$ is a set adjustable parameters (or weights) of i-th node of η-th layer of a neural network;

x' is a input features of reduced set of instances or features;

x is a set of instances (examples, cases);

x_j is a j-th input feature;

x'_i is a j-th input feature is a reduced set;

x^s is an s-th instance of a sample;

x^s_j is a value of j-th input (descriptive) feature of s-th instance;

$x_j^{(\eta,i)}$ is a j-th input value of i-th neuron of η-th layer of a neural network;

y is a set of values of output feature;

y' is an output feature for reduced set of instances;

y^s is a value of an output feature for s-th instance x^s;

y^{s*} is a calculated output feature value for the s-th instance on the model output;

y_i^s is a value of i-th output feature of s-th instance;

$y^{(\eta,i)}$ is an output value of i-th neuron of η-th layer of a neural network.

INTRODUCTION

Modern technical objects (in particular vehicles) are extremely complex and place high demands on reliability. This requires automation of condition monitoring and fault diagnosis of objects and their components. The predictive maintenance improves operational readiness of technical objects [1, 2].

The **object of study** is a technical object health and usage monitoring process.

The process of technical object health and usage monitoring involves measuring equipment characteristics, processing measurement data and determining the equipment state [3]. This may be provided by the HUMS, which is a sensor-based system that measure the health and performance of mission-critical components in diagnosed objects. It provides actionable information so that maintainers can make data-informed decisions [1].

The HUMS are widely used for condition monitoring of rotating equipment such as helicopters trucks or power plants. Typically, for vehicles the sensors placed on the equipment such as the transmission or the engine and then vibration measured and used to determine the state of the equipment or it's details [2].

The HUMS for helicopters may provide such benefits as: reduction in inspection times, unneeded maintenance, unscheduled and scheduled maintenance, unscheduled flight cancellation, test flights, vibration related wear damage and avionics removals, and increasing in safety, sense of safety, performance, mission, confidence, ease of troubleshooting, and morale [4].

The basis for automation of decision making in HUMS is the use of DM. The DM is a formalized description of diagnosing object required to solve the problems of diagnosis [3, 5].

To build diagnostic systems (particularly HUMS), it is possible to use the paradigms of model-based diagnosis (requires the presence of an analytical or physical model of the diagnosed object) [5] or data-driven diagnosis (based on the AI-model created on the set of observations) [6, 7].

Since vehicles are extremely complex systems that operate in changing conditions of an aggressive environment and are characterized by variability, the creating accurate analytical (physical) models for them is an extremely complex task. Therefore, in practice, the use of data-driven diagnosis methods is more convenient.

The **subject of study** is a methods of computational intelligence for data-driven model building and related data processing tasks for HUMS.

Model building based on computational intelligence [7] requires the availability of a sample of observations containing instances (cases, exemplars) of good and defective items or details.

The equipment faults are relatively rare in a practice. So the class-imbalanced training dataset should be used to train the model for fault detection.

The **purpose of the work** is to formulate data processing problems, to form a data set for data-driven model building and construct simple method for automatic DM building on example of helicopter HUMS.

1 PROBLEM STATEMENT

The instance (case, exemplar) is a set of data that describes the observation of an object (process) at a particular point in time. Instances are characterized by the values of features (attributes, properties).

The training sample is a sample on the basis of which the DM is built. The test sample is a sample used to test the performance of the DM.

The input data for DM building is a training sample $<x, y>$ characterized by N features set $\{x_j\}$, $j = 1, 2, ..., N$, consisting of S instances (examples, cases): $x = \{x^s\}$, $s = 1, 2, ..., S$, each of which described by the feature values $x^s=\{x^s_j\}$, where x^s_j is a value of j-th input (descriptive) feature of s-th instance, $y=\{y^s\}$ is a set of values of output feature, where y^s is a value of an output feature for s-th instance [7, 8].

The problem of dependency approximation: given: recognized instance x^s, model of the dependence $y=f(x)$,

DOI 10.15588/1607-3274-2025-1-11

find: y^s the estimated value of output feature for x^s. If the output variable is continuous then the problem of dependency approximation is a output real value estimation (regression). If the output variable is discrete then the problem of dependency approximation is a classification (pattern recognition).

During the process of DM building we typically need to address some of the following problems.

The problem of feature selection [9]: given: $<x, y>$, find: $<x', y>$, $x' \in \{x_j\}$, $N'<N$, $S'=S$, $f(<x', y>, <x,y>) \to$ opt.

The feature extraction problem (construction of artificial features): given: $<x, y>$, find: $<x', y>$, $x'=\{x'_i\}$, $x'_i = F_i(\{x_j\})$, $S'=S$, $f(<x', y>, <x, y>) \to$ opt.

The instance selection problem [9]: given: $<x, y>$, find: $<x', y'>$, $x' \in \{x^s\}$, $y'=\{y^s | x^s \in x'\}$, $S'<S$, $N'=N$, $f(<x', y'>, <x, y>) \to$ opt.

The problem of DM synthesis (model building) [8]: given: $<x, y>$, find: $<F(), w>$: $y^{s^*} = F(w, x^s)$, $f(F(), w, <x, y>) \to$ opt.

Particularly, for the case of feed-forward neural or integrated feed-forward neuro-fuzzy network basis the $<F(), w>$ defined as $<M, \{N_\eta\}, \{ y^{(\eta,i)}(x^{(\eta,i)}) \}>$ and described by the $y_i^s = y^{(M,i)}(y^{(M-1,i)}(....y^{(1,i)}(x^s)))$, $i=1,2,...,N_{\eta-1}$, $w^{(\eta,i)} = \{w_j^{(\eta,i)}\}$, $y^{(0,j)} = \psi^{(0,j)} = x_j^s$, $N_0 = N$, $x_j^{(1,i)} = x_j^s$, $i=1,2,...,N_{\eta-1}$, $\eta=1,2,...,M$, $j=1,2,...,N$.

Here $\{y^{(\eta,i)} = \psi^{(\eta,i)}(\varphi^{(\eta,i)})\}$ and $w = \{w^{(\eta,i)}\} = \{w_j^{(\eta,i)}\}$ are structural blocks and parameters of DM based on neural network, respectively.

The problem of DM simplification: given: $[<x, y>]$, $<F(), w>$, find: $<F'(), w'>$: $f(<F'(),w'>, <F(),w>, [<x, y>]) \to$ opt.

The problem of DM additional training: given: $<x', y'>$, $<x, y>$, $<F(), w>$, find: $<F'(),w'>$: $f(<F'(), w'>, <F(), w>, <x', y'>, <x, y>) \to$ opt.

For each problem considered above, it is possible to use a wide range of criteria for DM quality (performance) estimation [10, 11].However, in practice, criterion f usually defined on the base of model error function E.

In general case (for discrete and continuous outputs) we can use:

– MSE:

$$E = \frac{1}{S}\sum_{s=1}^{S}\left(y^s - F(x^s)\right)^2 ;$$

– SSE:

$$E = \sum_{s=1}^{S}\left(y^s - F(x^s)\right)^2 ;$$

– MAE:

$$E = \frac{1}{S}\sum_{s=1}^{S}\left|y^s - F(x^s)\right| .$$

In case of discrete output feature we can use an error formula:

$$E = \sum_{s=1}^{S}\{1 \mid y^s \neq F(x^s)\} \to \min .$$

For binary and discrete output features we can compute the probability estimates of decisions:

– of incorrect decision making: $P_{\text{incorrect}} = E/S$;

– of correct decision making: $P_{\text{correct}} = 1 - P_{\text{incorrect}}$.

2 REVIEW OF THE LITERATURE

The generalized system of technical diagnostics (in particular, HUMS) [1, 5, 6] is shown on the Fig. 1.

The signals from the diagnosed object are measured by the measurement devices and transformed into data in the computer memory through the input devices.

For example, in the tasks of diagnosing helicopter gears, the data set of observations is a large vibration data set.

The signal processing is performed and object's state is determined.

There are two main paradigms for the object's state determination. They are model-based diagnosis [5] and data-driven diagnosis [6].

Since the analytical (physical) model of the diagnosed object state is absent in many practical cases or is not enough accurate due to the lack of expert knowledge, the data-driven diagnostics [6] has become widely used in practice. It is used a sample of observations and based on constructing a model of diagnosed object state using machine learning methods and models (statistical [12], metric [13], soft computing [14, 15], logical [16], rule-based [17], and others). A comparative characteristics description of machine learning methods for constructing data-driven diagnostic models is given in Table 1. Here, for each comparison criterion, cells with the best content are highlighted with a green background, cells with the worst content are highlighted with a red background, and cells with average content are highlighted with a yellow background.

As can be seen from Table 1, there is no group of data-driven methods that would be the best by all criteria. Therefore, for each specific task, based on its characteristics and available resources, it is necessary to specifically solve the problem of selecting applicable methods, as well as the problem of choosing the best method among them.

Additionally, the optimization methods (hybrid, genetic [18], swarm [19], classic direct search and gradient methods [20]) have particular interest for different machine learning problems. These methods have a strong impact on the speed and accuracy of problem solving in the process of constructing a diagnostic model.

A significant impact on simplifying and accelerating the process of diagnostic model constructing, as well as reducing the complexity of the model and increasing its interpretability can be exerted by methods of data dimensionality reduction [21] applied to the sample before the model constructing.

DOI 10.15588/1607-3274-2025-1-11

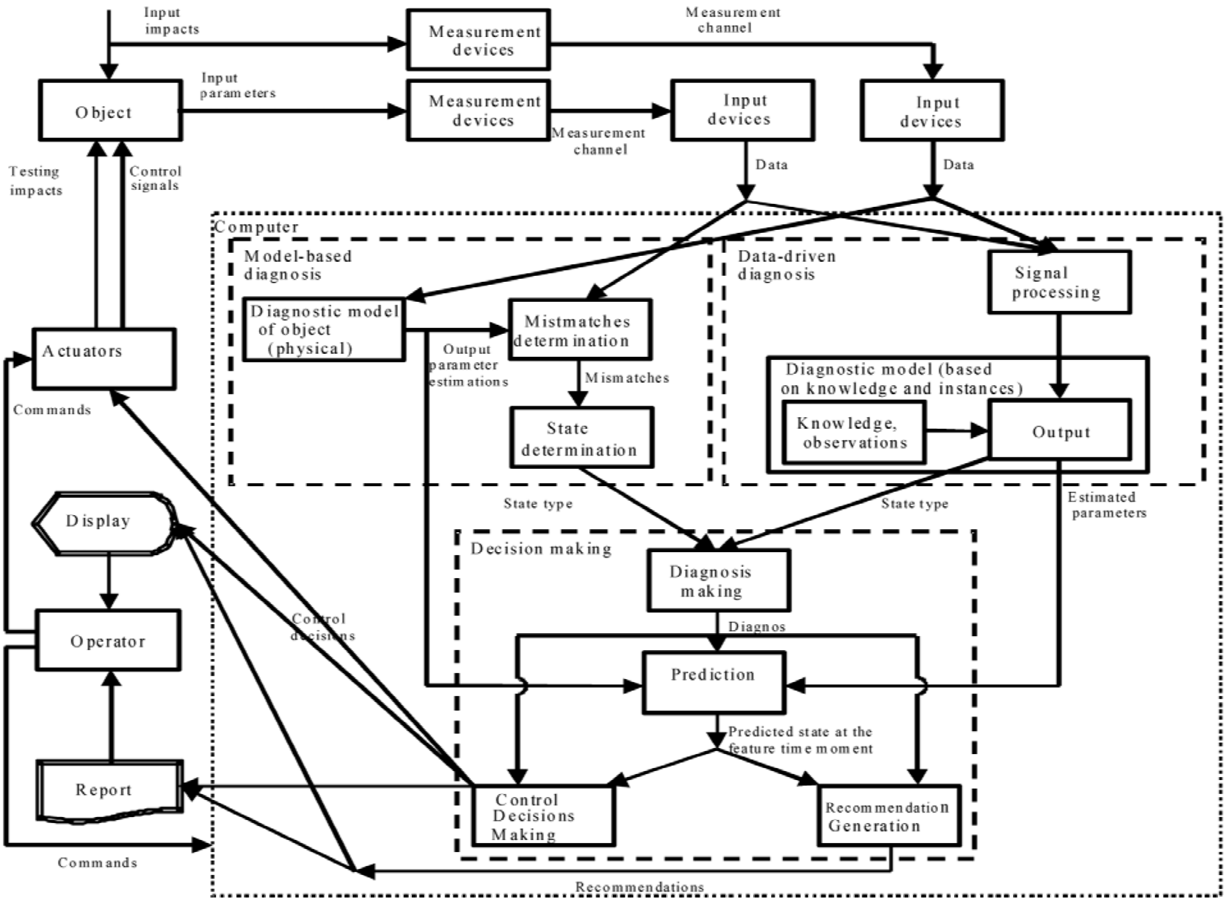

Figure 1 – Schema of generalized system of technical diagnostics

Methods of data dimensionality reduction include methods of the in formativeness estimation and selecting informative features (feature selection) [22, 23], methods of artificial features forming (feature extraction) [24, 25] including locality-sensitive hashing [26, 27], significance estimation and selection of instances (sample forming) [28, 29]. In addition, methods of digital processing and signal analysis (Fourier and wavelet transformation, statistical, spectral, cepstral analysis, etc.) [30–33] can be used to reduce the dimensionality of data.

Information about the structure of samples, useful for constructing models and solving related problems, can be provided by cluster analysis methods [34]. Cluster analysis or clustering is the task of grouping a set of objects (instances) in such a way that objects in the same group (called a cluster) are more similar (in some sense) to each other than to those in other groups (clusters).

Additional information can also be provided by data mapping and visualization methods. Known data visualization methods [35] seem to be extremely computationally complex and their application to large volumes of data can be difficult.

This paper considers the problem of creating a simple heuristic method for data mapping and visualization, data dimensionality reduction and DM building, that does not require solving optimization problems and complex calculations.

3 MATERIALS AND METHODS

Since generally the data sample is multidimensional and the number of features is much greater than three, its visualization is an extremely difficult task. The use of various data transformation methods will also require extremely large computational resources. And the process of building a model will also be extremely resource-intensive.

Therefore, it is proposed to use a combined approach to solving the problem, combining a simple transformation of data from a multidimensional space to a two-dimensional one, which will allow, on the one hand, to visualize a data sample, and, on the other hand, will significantly reduce the dimensionality of the data and will significantly simplify and speed up the process of building diagnostic models, as well as reduce their complexity and the number of adjustable parameters. The model simplifying will also improve their interpretability and generalizing properties.

Let consider a heuristic approach that involves mapping the sample from the original space of N features into a two-dimensional space of artificial features. These features will essentially be similar to locality-sensitive hashes defined without solving the optimization problem, based on the hypothesis of compactness of the arrangement of classes.

DOI 10.15588/1607-3274-2025-1-11

Table 1 – Comparative characteristics of the groups of data-driven methods of diagnosis

Group of methods	Statistical	Separation in the feature space	Metrical	Based on soft computing			Based on assumption of class of decision functions	Logical	Rule-based expert systems
				Neural networks	Neuro-fuzzy networks	Fuzzy models			
Input data required for DM synthesis:									
– training set	+	+	+	+	+	–	+	+	–
– human expert knowledge	–	–	–	–	–	+	–	–	+
– model architecture	–	–	–	+	+	+	–	–	–
– other	Density distribution of feature values	–	Metric type	–	–	–	Type and quality functional of the decision function	–	–
Specific requirements to the task	Knowledge of the distribution of feature values and their densities	The need to transform the feature space	High informative features	–	Formation of fuzzy terms and their membership functions	Formation of fuzzy terms and their membership functions	Orthonormality of feature system	Discrete and categorical data	Consistency and completeness of knowledge
The requirement for compactness of classes	–	+	+	–	–	–	+	–	–
Processing of complex symbolic data	–	–	–	–	–	+	–	+	+
Applicability to large-scale feature space problems	+	+	+	+	+	–	–	–	–
Applicability poorly studied subject areas	–	+	+	+	+	–	–	+	–
Interoperability of DM	Low	Low	Low	Low	High	High	Middle	High	High
Automatic generalization of data	Low	High	High	High	Middle	Low	Low	Low	Low
The level of automation of DM building	High	High	High	Middle	Middle	Low	High	High	Low
Adaptiveness	Middle	High	High	High	Middle	Low	Middle	Low	Low
The need for a large amount of observations	+	–	–	–	–	–	–	–	–
The computational complexity of DM building	High	Middle	Middle	High	Middle	Low	High	High	Low
The use of local search in the DM construction	–	–	–	+	+	–	+	–	–

For the given training sample $<x, y>$, where $y \in \{0, 1\}$, find coordinates of class centers (etalons as averaged instances representing corresponding classes):

$$C_j^q = \frac{1}{S^q}\sum_{s=1}^{S}\{x_j^s \mid y^s = q\},\ j = 1, 2, ..., N,\ q=0, 1,$$

as well as the sum by the coordinates:

$$C_j^+ = \frac{1}{S}\sum_{s=1}^{S}\{x_j^s\},\ j = 1, 2, ..., N,$$

and the average of the class centers:

$$C_j^{avg} = \frac{C_j^0 + C_j^1}{2},\ j = 1, 2, ..., N.$$

For each s-th instance of a sample, s = 1, 2, ..., S, determine the distance from it to the sample center C^+ or to the center of each class C^q, q=0, 1, or to the average of class centers:

– as an Euclidean distance:

$$d^s(x^s, C) = \sqrt{\sum_{j=1}^{N}\left(x_j^s - C_j\right)^2},$$

– as a cosine of angle between vectors:

$$d^s(x^s, C) = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} x_i^s C_j}{\sqrt{\sum_{i=1}^{N}\sum_{j=1}^{N} x_i^s x_j^s}\sqrt{\sum_{i=1}^{N}\sum_{j=1}^{N} C_i C_j}}.$$

Here as C we conventionally note the center relative to which the distance is determined.

There are many other methods of determining distances that can be used.

Map the sample $\{<\{x_j^s\}, y^s>\}$ to the tow-dimensional coordinate system: $\{<d^s(C^p), d^s(C^q), y^s>\}$, where y^s used as class label to marking instances.

Such a two-dimensional coordinate system will allow to visualize data sample and to estimate complexity of a problem.

If the separation of classes in a two-dimensional coordinate system be close to linear, then it seems possible to

DOI 10.15588/1607-3274-2025-1-11

use a modification of the metric classification method based on class centers.

The basic metric classification method assumes that at the training stage, class centers are defined in the system of original features as average coordinates of instances of the corresponding classes, and at the recognition stage, the recognized instance is assigned to the class whose distance to the corresponding class center from the given instance is the smallest.

Unlike the basic method, the initial set of features (signal acquisitions) is proposed to be replaced by distances in a two-dimensional coordinate system. This will significantly reduce the dimensionality of the data set, as well as make the model extremely simple.

The modified metric classification method can be formulated as such set of stages.

Phase of model training.

Stage 1. Initialization. Give a training data set <*x*, *y*> in original *N*-dimensional set of features. Specify the method of *C* and *d* computing.

Step 2. Model Building. Using given data set <*x*, *y*> compute class centers $\{C^q\}$ as a DM parameters.

Phase of recognition.

Stage 1. Initialization. Give data set <*x*, *y*> in original *N*-dimensional set of features and. Provide DM parameters (*C* coordinates) and *d* computing method.

Stage 2. Data Mapping. Using specified method of *C* computing map the sample $\{<\{x^s_j\}, y^s>\}$ to the two-dimensional coordinate system: $\{<d^s(C^p), d^s(C^q), y^s>\}$.

Step 3. Decision Making. For each recognized instance x^s the decision on it's classifying can be computed using the formula:

$$y^s = \arg\min_{p,q}(d^s(x^s, C^p), d^s(x^s, C^q))$$

or the same in other form:

$$y^s = \{p \mid d^s(x^s, C^p) \le d^s(x^s, C^q)\}.$$

Such idea may be used also for a feed-forward neural network building. Simple shallow two-layer feed-forward neural network (Fig. 2) [36] may be constructed and trained in a non-iterative mode using following method.

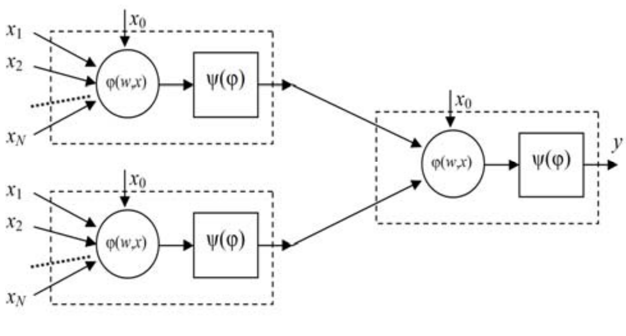

Figure 2 – Schema of the two-layer feed-forward neural network

The network input is a set of original *N* features $\{x_j\}$. Each *i*-th neuron of a η-th layer of a network perform computation: $y^{(\eta,i)} = \psi^{(\eta,i)}(\varphi^{(\eta,i)})$.

The first hidden layer of a network is represented by two neurons mapping instances from the original feature space to the two dimensional space. Each neuron has discriminative (postsynaptic) function Euclidean distance:

$$\varphi^{(1,i)} = \sum_{j=1}^{N}(x_j - w_j^{(1,i)})^2,\ i = 1, 2,$$

and transfer (activation) function Gaussian:

$$\psi^{(1,i)}(a^2) = \exp(-a^2),$$

or sigmoid:

$$\psi^{(1,i)}(a) = \frac{1}{1+\exp(-a)},$$

or pure linear:

$$\psi^{(1,i)}(a) = a.$$

First neuron compute distance from the recognized object to the C^0 and the second neuron computes distance to the C^1. So weights of first neuron will be equal to the values of C^0 coordinates, and the second neuron weights will be equal to the values of C^1 coordinates:

$$w_j^{(1,i)} = C_j^{i-1},\ j = 1, 2, ..., N; i = 1, 2.$$

The second layer of a network contains one neuron, which separates classes in a two-dimensional space of distance coordinates. This neuron use weighted sum as discriminative (postsynaptic) function:

$$\varphi^{(2,1)} = w_0^{(2,1)} + \sum_{j=1}^{2} w_j^{(2,1)} \psi^{(1,j)},$$

DOI 10.15588/1607-3274-2025-1-11

and hard-lim (Heaviside step) function as a transfer function:

$$\psi^{(2,1)}(a) = \begin{cases} 0, a < 0; \\ 1, a \geq 0, \end{cases}$$

or as a sigmoid function:

$$\psi^{(2,1)}(a) = \frac{1}{1+\exp(-a)}.$$

The weights of this neuron may be evaluated using the formula:

– for the case, when first layer neurons use Gaussians:

$$w_j^{(2,1)} = \begin{cases} 0, j = 0; \\ 1, j = 1; \\ -1, j = 2; \end{cases}$$

– for the case, when first layer neurons use sigmoid or pure linear:

$$w_j^{(2,1)} = \begin{cases} 0, j = 0; \\ -1, j = 1; \\ 1, j = 2. \end{cases}$$

After network creation it is possible to adjust it's parameters to improve it's accuracy, if needed, or for additional training, when additional set of training instances should be used. For this purpose, the steepest descent method [20] with a backpropagation technique [37] or evolutionary search methods may be used.

4 EXPERIMENTS

Let's consider a real problem of constructing a diagnostic model for diagnosing helicopter gears.

Detection of gear faults is challenging. Undetected gear faults can result in catastrophic gearbox failures, which depending on the criticality of the application, can be life threatening. For vibration monitoring, it is identifying a feature within the background noise of a gearbox which is indicative of fault. For critical system, the risk is a missed detection that allows a mission to proceed when it should be aborted.

The data set provided by GPMS Inc., USA contains 1158 raw vibration signals measured for helicopter gears. The roughly two-thirds of these instances are nominal data while the other third have a gear fault. Each sample instance provided as an input signal represented by 93752 acquisitions (discrete counts) associated with a value of the output binary variable representing class of the instance: good (nominal) or bad (having a gear fault).

The examples of graphs for good and bad gear signals and their parameters are shown at Fig. 3. As can be seen from Fig. 3, the signal parameters [2] can be used to construct a decision-making model for the signal belonging to one of two classes. However, determining these parameters requires significant computational resources and requires solving the problem of selecting informative features among the signal parameters.

Therefore, we will use the method proposed in this paper, which maps instances into a two-dimensional space with subsequent construction of a DM for a two-dimensional data sample.

As a main indicator for method or model performance evaluation we should use a model error probability estimation (percent of incorrect decisions) or model correct decision probability estimation (percent of correct decisions).

5 RESULTS

The fragment of the results of conducted experiments is presented at Fig. 4–Fig. 9. Here the C^+ designated as C, and C^{avg} designated as C^m.

As it can be seen from Fig. 4–Fig. 9, the proposed method allows map multidimensional data into two-dimensional space, ensuring linear separability of classes in a two-dimensional space. On the one hand, it allows visualizing data and getting view on the number and shape of clusters, as well as the significance of instances, and, on the other hand, clearly confirms the possibility of using the proposed method for constructing a DM in the problem of diagnosing helicopter gears.

For the experimental study of the applicability of the proposed method for DM building the training and test samples were formed from the initial sample by randomly selecting instances of each class, maintaining the ratio of the shares of classes in the initial sample. Then for the obtained training samples, DM were constructed based on the proposed method, which were tested on the corresponding test samples. The results of experiments are given in Table 2.

Table 2 – Results of experiments on constructing DM based on the proposed method

S_{train}	S_{test}	$P_{incorrect\ train}$	$P_{incorrect\ test}$
10	1148	0	0/0043
50	1108	0	0.0009
100	1058	0	0
250	908	0	0
500	658	0	0

As can be seen from Table 2, the proposed method allows obtaining highly accurate DM even with small training samples, provided that the frequency of classes in the samples is preserved.

DOI 10.15588/1607-3274-2025-1-11

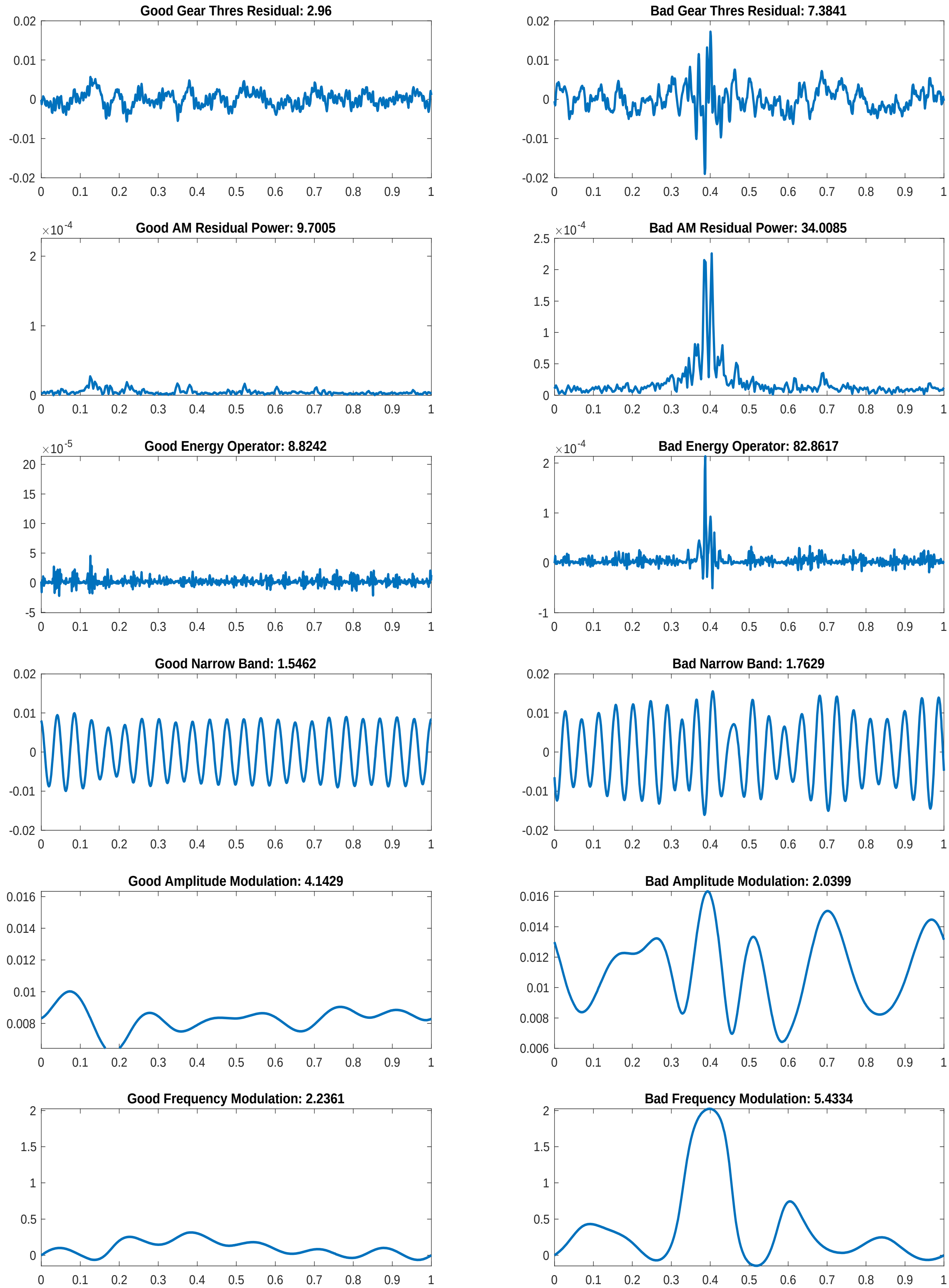

Figure 3 – Examples of graphs for good and bad gear signals and their parameters

DOI 10.15588/1607-3274-2025-1-11

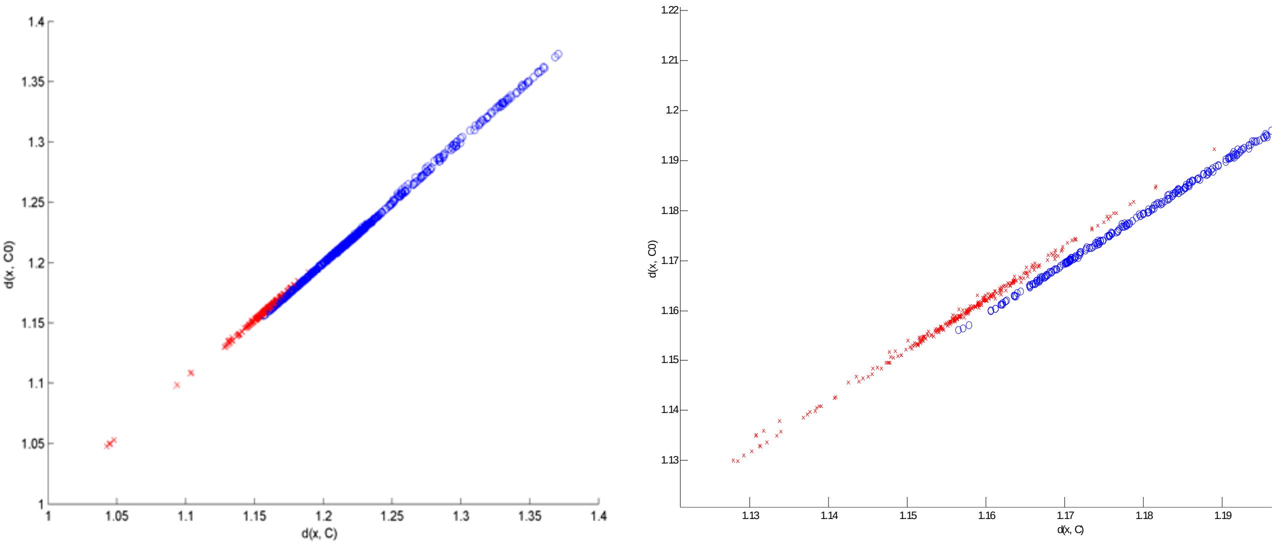

Figure 4 – Dataset in the $d(x, C^{+})$ and $d(x, C^{0})$ coordinate system

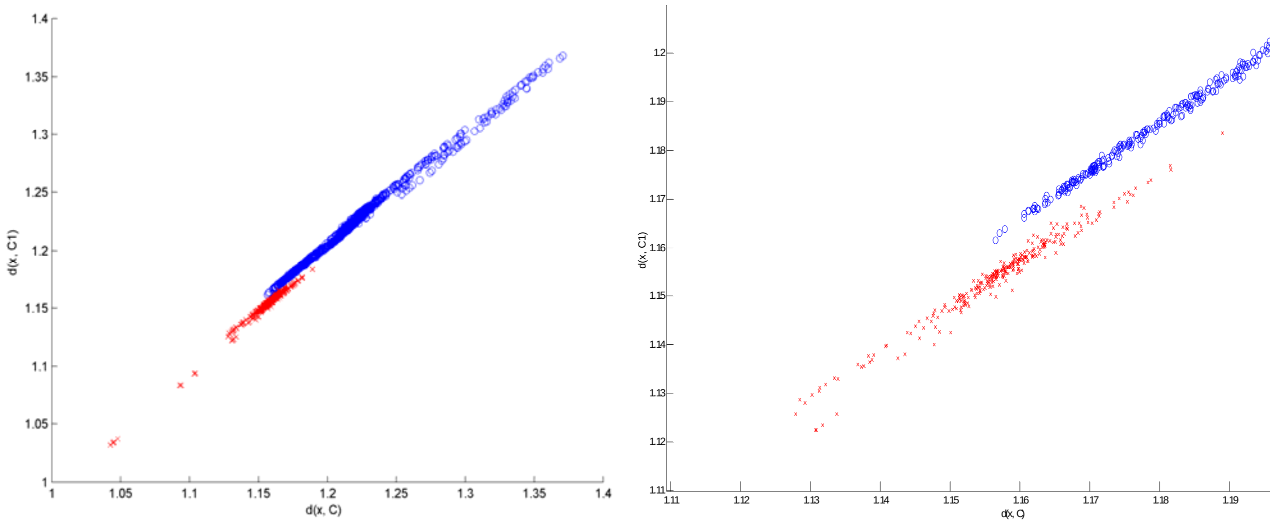

Figure 5 – Dataset in the $d(x, C^{+})$ and $d(x, C^{1})$ coordinate system

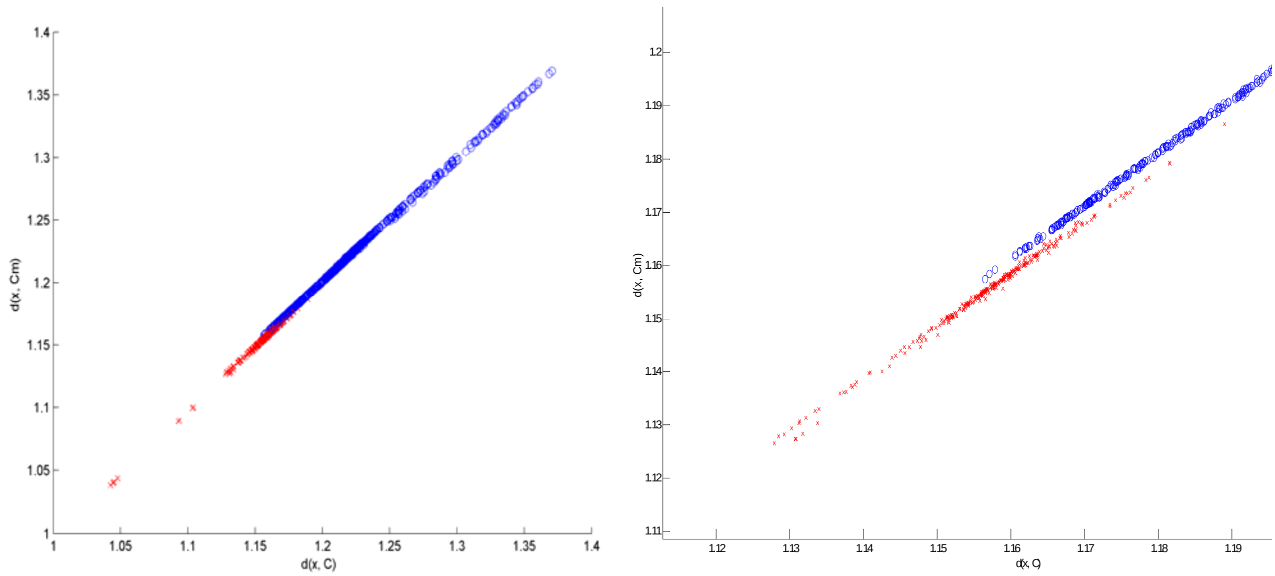

Figure 6 – Dataset in the $d(x, C^{+})$ and $d(x, C^{avg})$ coordinate system

DOI 10.15588/1607-3274-2025-1-11

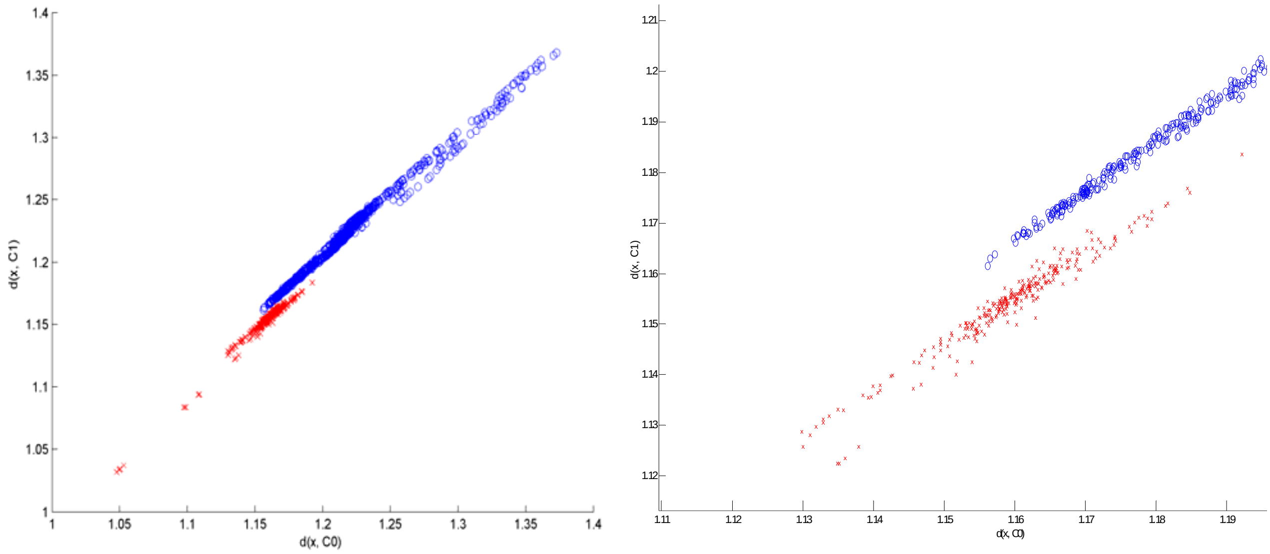

Figure 7 – Dataset in the $d(x, C^0)$ and $d(x, C^1)$ coordinate system

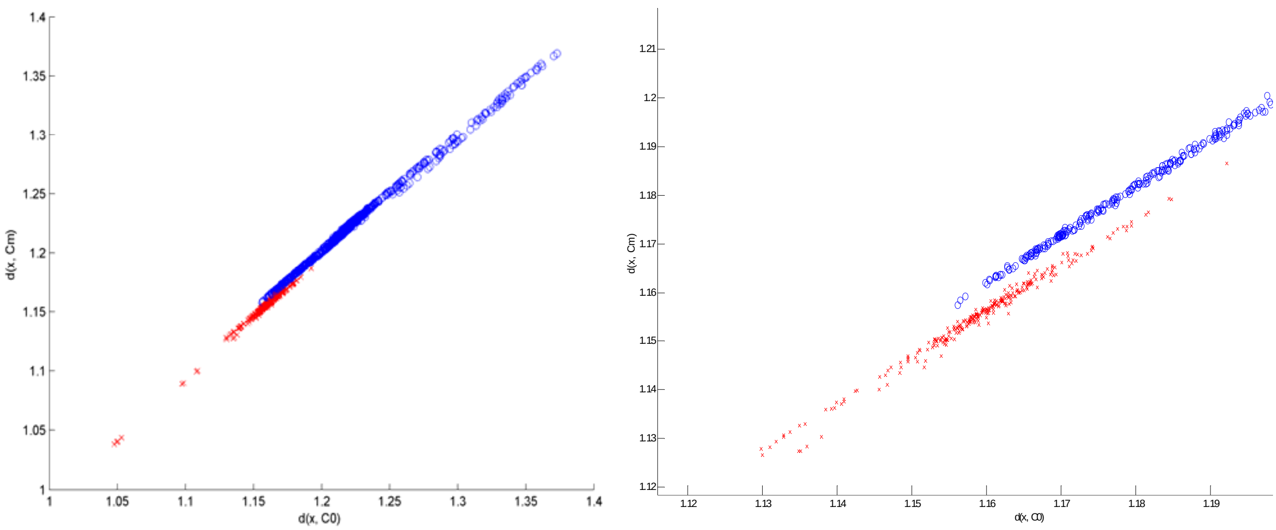

Figure 8 – Dataset in the $d(x, C^0)$ and $d(x, C^{avg})$ coordinate system

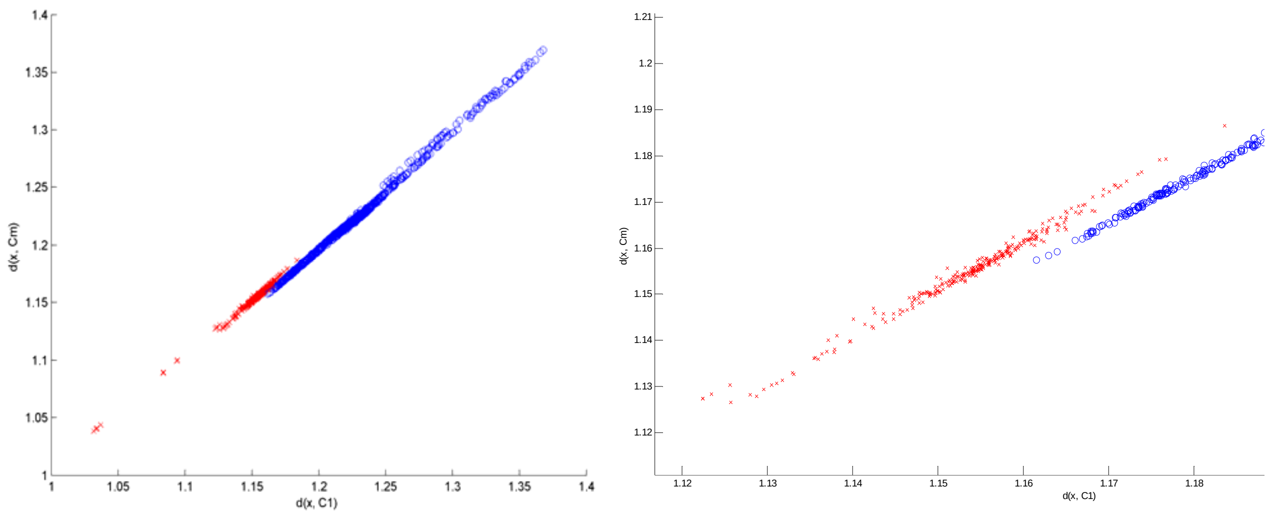

Figure 9 – Dataset in the $d(x, C^1)$ and $d(x, C^{avg})$ coordinate system

DOI 10.15588/1607-3274-2025-1-11

6 DISCUSSION

The results of conducted experiments allow to conclude that the proposed method provides a significant reduction in the data dimensionality (in particular, for the considered problem of constructing a DM for helicopter gear diagnosis, it reduces the data dimensionality due to the compression of features by 46876 times).

Additionally, it may be of interest to study a possible combination of the proposed method with methods for sample forming using metrics of the value of instances. As the results of the conducted experiments for randomly selected instances in a two-dimensional system of artificial features obtained on the basis of the proposed method showed a significant reduction of the sample for individual tasks may allow to provide acceptable accuracy. And taking into account individual estimates of the instance significance will allow, even for small samples, to ensure the topological representativeness of the formed sample in relation to the original sample.

CONCLUSIONS

The urgent problem of data-driven diagnostic model constructing for decision-making automation in health and usage monitoring process is considered in the paper.

The scientific novelty of obtained results is that a method is proposed for the mapping of multidimensional data into a two-dimensional space preserving local properties of class separation, allowing for the visualization of multidimensional data and the production of simple diagnostic models for the automatic classification of diagnostic objects. A method for synthesizing diagnostic models based on a two-layer feed-forward neural network is also proposed, which allows obtaining models in a non-iterative mode.

The practical significance of obtained results is that a sample of observations of the state of helicopter gears was obtained, which can be used to compare data-driven diagnostic methods and data processing methods that solve the problems of data dimensionality reduction. Mathematical support has been developed that allows displaying a sample from a multidimensional to a two-dimensional space, which makes it possible to visualize data and reduces the dimensionality of the data. Diagnostic models have been obtained that allow automating the decision-making process on whether the diagnosed object (helicopter gear) belongs to one of two classes of states.

The prospects for further research are to compare methods for constructing data-driven models, as well as methods for reducing the dimensionality of data based on the proposed sample. Additionally, it may be of interest to study a possible combination of the proposed method with methods for sample forming using metrics of the value of instances.

ACKNOWLEDGEMENTS

The Dataset used in experiments were provided by the GPMS Inc, USA. The work is supported by the National University “Zaporizhzhia Polytechnic” and supported by the international projects of WORK4CE: Cross-domain competences for healthy and safe work in the 21st century (Project Reference: 619034-EPP-1-2020-1-UAEPPKA2-CBHE-JP) of the ERASMUS+ programme of the European Union and ViMaCs: Virtual Master Cooperation Data Science Project-ID: 57513461 (Phase 1), 57602060 (Phase 2) of the DAAD.

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Received 09.12.2024.
Accepted 06.02.2025.

DOI 10.15588/1607-3274-2025-1-11

УДК 004.93

ПОБУДОВА ДІАГНОСТИЧНОЇ МОДЕЛІ, КЕРОВАНОЇ ДАНИМИ, ДЛЯ МОНІТОРИНГУ СПРАВНОСТІ ТА ВИКОРИСТАННЯ СПОРЯДЖЕННЯ ГЕЛІКОПТЕРІВ

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АНОТАЦІЯ

Актуальність. Сучасні технічні об'єкти (зокрема транспортні засоби) є надзвичайно складними та висувають великі вимоги до надійності. Це потребує автоматизації моніторингу стану та діагностування несправностей об'єктів та їх складових. Прогнозне обслуговування підвищує експлуатаційну готовність технічних об'єктів. Об'єктом дослідження є процес моніторингу справності та використання технічних об'єктів. Предметом дослідження є методи обчислювального інтелекту для побудови керованої даними моделі та відповідні завдання опрацювання даних для системи моніторингу працездатності та використання.

Мета. Мета роботи – сформулювати задачі обробки даних, сформувати набір даних для побудови керованої даними моделі та побудувати простий метод автоматичної побудови діагностичних моделей на прикладі системи моніторингу стану та використання гелікоптерів.

Метод. Запропоновано метод для відображення багатовимірних даних у двовимірний простір із збереженням локальних властивостей поділу класів, що дозволяє візуалізувати багатовимірні дані та створювати прості діагностичні моделі для автоматичної класифікації об'єктів діагностування. Запропонований метод дозволяє отримати високоточну діагностичну модель з малими навчальними вибірками за умови збереження частоти класів у вибірках. Запропоновано також метод синтезу діагностичних моделей на основі двошарової нейронної мережі прямого поширення, що дозволяє отримувати моделі в неітеративному режимі.

Результати. Отримано вибірку спостережень стану механізмів вертольота, яку можна використовувати для порівняння методів діагностування, керованого даними, та методів опрацювання даних, які вирішують задачі скорочення розмірності даних. Розроблено програмне забезпечення, яке дозволяє відображати вибірку з багатовимірного простору в двовимірний, що дає змогу візуалізувати дані та зменшує розмірність даних. Отримано діагностичні моделі, які дозволяють автоматизувати процес прийняття рішення про належність діагностованого об'єкта (спорядження вертольота) до одного з двох класів станів.

Висновки. Результати проведених експериментів дозволяють зробити висновок, що запропонований метод забезпечує суттєве зниження розмірності даних (зокрема, для розглянутої задачі побудови моделі діагностування вертолітного обладнання зменшує розмірність даних за рахунок стиснення ознак у 46876 разів). Оскільки результати проведених експериментів для випадково вибраних екземплярів у двовимірній системі штучних ознак, отриманих на основі запропонованого методу, показали значне скорочення вибірки для окремих завдань, це може дозволити забезпечити прийнятну точність. А врахування індивідуальних оцінок значущості екземплярів дозволить навіть для малих вибірок забезпечити топологічну репрезентативність сформованої вибірки по відношенню до вихідної вибірки.

Перспективи подальших досліджень полягають у порівнянні методів побудови моделей, керованих даними, а також методів зменшення розмірності даних на основі запропонованої вибірки. Крім того, може становити інтерес дослідження можливого поєднання запропонованого методу з методами формування вибірки з використанням метрик значення екземплярів.

КЛЮЧОВІ СЛОВА: діагностування на основі даних, система моніторингу працездатності та використання, зменшення розмірності даних, класифікація.

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DOI 10.15588/1607-3274-2025-1-11