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CONSTRUCTION OF THE DIAGNOSTIC MODEL BASED ON COMBINING SPECTRAL CHARACTERISTICS OF NONLINEAR DYNAMIC OBJECTS

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ABSTRACT

The task of constructing diagnostic models for nonlinear dynamics objects solved in this work. The reasons for increasing the dimension of the modern diagnostics objects description and related problems of using existing diagnostics methods are considered. The purpose of this work is to increase the accuracy and reliability of nonlinear dynamic objects diagnosing by forming diagnostic models in the conditions of increasing the dimension of the objects description for creating effective tools for automated systems of technical diagnostics. It is offered a broad overview and classification of methods for reducing the dimension space of diagnostic features including nonlinear dynamic objects with continuous characteristics and unknown structure, which can be considered as a "black box". The forming diagnostic models method of nonlinear dynamic objects based on the combination of spectral characteristics obtained as the result of continuous models transformations: wavelet transformations coefficients and models moments of different orders is proposed. The family of diagnostic models is proposed as combinations of dynamic objects spectral characteristics with weak nonlinearity. The hybrid method of forming diagnostic models based on the combination of spectral characteristics suggested. The method consist of sequential application of feature filtering for forming primary feature space, construction of secondary feature space using the spectral transformations and diagnostic model construction by complete bust of secondary features. It is developed a detailed algorithm for constructing diagnostic models using the proposed hybrid method. The suggested method has been tested on real-life task of diagnosing a non-linear dynamic object – a electric motor. Primary diagnostic model of the electric motor taken on the base of indirect measurements of the air gap between the rotor and the stator of the motor. Diagnostic models constructed by combining the spectral characteristics of continuous models. The diagnostic models family of the switched reluctance motor is offered. The method is demonstrate more independence of the accessibility indicator then existing methods of the diagnostic feature space biulding: the samples, the moment and the coefficients of wavelet transformations of the primary diagnostic models.

Keywords: Nonlinear Dynamic Objects; Diagnostic Models; Model Reduction; Spectral Transformations

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INTRODUCTION

With the increasing complexity of modern objects and conditions of their operation in various industries, medicine, economy, the role of automated systems of technical diagnostics (ASTD) in the tasks of timely and reliable determination of the technical condition type of diagnostics objects (DO) concerning the assessment of product quality, minimization is increasing. maintenance costs, etc.

These processes lead to the active development of technical diagnostics (TD) tools and methods [1-2]. The great interest are the tasks of indirect control and diagnosis of complex objects around the world, based on nonlinear dynamic objects with continuous characteristics and unknown structure, which can be considered as a "black box" [3, 4].

The use of existing ASTD is limited by the contradiction between the accuracy of diagnosis and the promptness of adjusting ASTD when using diagnostic models of large dimensions. The large dimensions and volumes of primary diagnostic information accumulate provide high accuracy of diagnosis, but this increases computational complexity and reduces the speed of ADST setup. Reducing the dimensionality and volume of primary identification information increases the speed of ADF setup, but reduces the accuracy of diagnosis.

The solution to this contradiction is a promising and urgent scientific and technical problem, which can be solved by constructing diagnostic models of significantly smaller dimension (reduction of information models), which provide high accuracy of diagnosis.

The purpose of the work is to increase the accuracy of diagnosing nonlinear dynamic objects by forming diagnostic models in the context of increasing the dimension of the description of the diagnostic objects to create effective diagnostic tools.

LITERATURE REVIEW

By 2010, the typical practical problems of forming diagnostic models were limited to dimensions of several dozen features, usually not more than 40 [5]. The situation has changed significantly over the last decade. The global volume of data increases more than twice every two years [6]. However, large amounts of data open up new opportunities.

The main reasons for this growth are technological advances and significant advances in DataScience and BigData [7]. New technologies have reduced the cost of creating, collecting, classifying and managing information tenfold.

The concept of the Digital Universe and large amounts of data have been the driving force behind fundamental changes in social life, technology, science and the economy. Significant advances in these areas stimulate the development of applied diagnostics problems with the dimension of the vector of signs of DO in hundreds and even thousands of units.

An example of a new challenge in the field of modern industrial technologies of the Industry-4.0 level is to improve the process of diagnosing components of technological equipment, in particular, electric motors [8], which actuate actuators. The magnitude of such a task increases dramatically, bearing in mind that significant amounts of technical information have been accumulated over the years of monitoring and control systems.

In the face of a sharp increase in the dimension of tasks, the initial diagnostic data (primary diagnostic information) is accompanied by the presence of many redundant variables and a small number of training examples, which negatively affects the accuracy of diagnosis and the speed of learning ASTD. Therefore, it is necessary to review the effectiveness of traditional methods of forming diagnostic models of DO.

An effective way of solving such problems is to reduce the space of primary features – a technique of preliminary data processing in the widely used data mining [5, 6], [7], [9].

There are many potential benefits of this approach: facilitating data visualization and comprehension, reducing measurement and storage requirements, reducing ASTD learning time and diagnosis, and improving overall machine learning algorithm performance.

This paper is an analytical review of existing approaches to solving problems of reducing diagnostic models and substantiating the use of spectral characteristics for the construction of diagnostic models of DO with continuous nonlinear dynamic characteristics and unknown structure, which can be considered as a “black box”.

RESEARCH MATERIALS

Traditional approaches to forming diagnostic models can be divided into three categories [7]: feature filtering, wrapping methods, and feature embedding.

Feature filtering. Formation of diagnostic models based on feature filtering consists in ranking the features by certain evaluation criteria [7], [9, 10], [11, 12], [13, 14], [15, 16], [17].

This approach provides less time quadratic complexity. These methods produce fast and efficient results, which is important when processing large amounts of data. In addition, the construction of diagnostic models does not depend on the chosen algorithm of learning ASTD and is performed before its implementation.

A limitation of this approach is that it evaluates the individual diagnostic value of each trait, without taking into account the relationship between individual low-informative traits, which together may have good diagnostic value [11].

In addition, the disadvantage of this approach is that its effective use requires a large amount of a priori data, therefore, it is oriented towards the operation of DO in certain operating modes and ranges of external conditions. Expanding the scope of practical applications, adapting to new functional requirements, operating in a wide range of external conditions leads to an increase in the a priori uncertainty of the data about the object, and therefore, to the reliability of diagnosis.

Wrapper of features. This approach provides for the formation of diagnostic models, using them to evaluate the ASTD learning algorithm that will be used in the diagnosis process [18, 19], [20].

When looking for the best solution, a complete search of all possible combinations of features is possible, if their number is not very large. This problem is NP-complex [21], and the search is difficult to realize when increasing the number of features describing DO. To overcome this drawback and to ensure efficiency of the wrapping method for a large number of traits describing DO, several search strategies are used, including genetic algorithms [21] and short-cut search methods [22] with direct extension and backward extraction of

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features of the diagnostic model. In direct selection, variables are gradually included in larger and larger subsets of traits, whereas in the case of retrieval, the set of traits is first considered, from which the least valuable traits are gradually withdrawn.

The main advantage of the approach over feature filtering is that it allows to consider dependencies between the features and to form the most valuable combinations of features for the ASTD learning algorithm [20].

The disadvantage of this approach is the need to re-teach ASTD when changing the ASTD learning algorithm. In addition, the approach is prone to retraining on small training datasets.

Embedding features. This approach is to select valuable combinations of diagnostic features at the same time as the learning process [23].

The computational complexity of embedding methods is less than that of wrapping methods, but greater than that of feature filtering. These methods are quicker to reach the solution, avoiding the retraining of the ASTD for each test subset of features compared to the wrapping methods. Also, embedding methods are less prone to retraining than wrapping methods. The main limitation of embedding methods is that they form a space of diagnostic features depending on the classifier. Therefore, the choice of the diagnostic model depends on the hypothesis that the classifier makes and is not suitable for other classifiers [24].

In view of the above, a tabular study of existing approaches to the formation of diagnostic models of ASTD was performed (Table 1).

In many tasks, reducing the dimensionality of data by selecting a subset of primary attributes is an important consideration in terms of processing and interpreting the results. If these considerations are not of fundamental importance, other ways of reducing the dimensions of diagnostic models are often considered. Better results are often achieved with secondary features derived from primary transformations [9,10]; [15], [25].

The selection of secondary features thus creates diagnostic models as a function of the primary features, while the selection of features returns subsets of the primary features.

There are a number of common methods for constructing features, including: basic linear transformations and more complex nonlinear input transformations.

A tabular study of existing approaches to the construction of ASDT diagnostic models is presented in Table 2.

When solving practical problems, the application of any method often does not lead to the desired results. The reason for this is, first and foremost, the greater or less a priori uncertainty of the DO, the causes of which are the complexity of the object (dynamic objects of different physical nature, including continuous nonlinear characteristics) and insufficient study of the processes occurring in it, as well as the presence of a large number of disturbing influences and obstacles to the environment.

Currently, many authors use hybrid methods, consisting of a combination of the approaches considered, the results of which are promising.

Hybrid approach. Recently, this is one of the popular approaches for forming diagnostic models. The hybrid approach combines several methods to take advantage of each of them to produce satisfactory TD results. This approach usually provides a fairly high diagnostic accuracy with low computational complexity.

A hybrid approach to feature selection based on consistent application of filtering and wrapping techniques is an effective practice. In the first stage of this approach, the most valuable subset of features is selected by the method of filtering - global search of the subset of features. At this stage, the number of considered features is reduced to several tens. In the second stage, the choice of the optimal from the point of view of the reliability of diagnosing a subset of features by the method of wrapping - local search for a subset of features. This approach is well-scalable for datasets consisting of many attributes.

This paper proposes a hybrid method of constructing diagnostic models based on a combination of spectral characteristics.

Hybrid method of forming diagnostic models based on the combination of spectral characteristics

An effective method of describing nonlinear and dynamic DO properties in the form of a feature vector **x** is the parameterization of continuous nonlinear and dynamic DO models $f(t)$. In this case, the function $f(t)$ is represented by the vector of diagnostic features $\mathbf{x} = (x_1,\ldots, x_n)$. Diagnostic features can be obtained by pre-converting T_j: $C[a, b] \to R^n$, $(j = 1,\ldots, n)$: $x_j = T_j(f(\tau_1,\ldots, \tau_k))$; where $C[a, b]$ – is the space of real continuous functions $f(t)$ given by the segment $[a, b]$; a, b – are some real numbers. As an operator T_j, orthogonal decompositions and integral transformations of continuous models into vectors of coefficients of basis functions can be used.

In practice, it is customary to use the sampling operator as T_j:

$$x_j = f(t_j), \quad t_j = j\Delta t, \tag{1}$$

where Δt – sample step

Modern subsystems of registration of the information which are a part of ASTD are capable to make hundreds and even thousands of measurements of responses DO in a second that provides completeness of primary diagnostic data. In this case, the measurement results are accompanied by the abundance of excess data. Moreover, it is obvious that the value of different sites of measured DO responses for the diagnosis procedure is different. In [15], [25] it is shown that the most informative regions of DO responses are usually the regions carrying the highest signal energy. In view of the above, the use of a signal sampling operator to form a space of diagnostic features is a little effective technique.

Another problem of constructing diagnostic models of nonlinear dynamic DO is the lack of “flexibility” of methods. To build diagnostic models of continuous DO, it is a good practice to choose spectral transformation methods. However, often, especially when dealing with nonlinear dynamic DO, it is necessary to evaluate both “local” signal characteristics and “global” characteristics to effectively use all the initial data. For example, wavelet transformations are oriented to evaluate the “local” characteristics of the signal, while the moments of the signals represent its “global” properties.

Table 1. **Investigation of existing approaches to diagnostic models selection for ASTD**

An approach to feature selection	**Feature selection algorithms**	**The main characteristics of the approach**	**Advantages / limitations of the approach**	**Criteria for the model value**
Filtering	• Component analysis • Information analysis • Extraclass / Intraclass distance • Correlation analysis	• Based on internal data properties • Runs once • Performs before applying the model training algorithm • Selects attributes regardless of classifier	*Advantages* • Low computational complexity • High decision speed • Convenience of handling large amounts of data *Limitation* • Does not take into account the relationship between the features • Does not guarantee a better solution: may miss out on features that are valuable in combination with other features	Statistical tests
Wrapping	• Complete bust • Quasi-complete bust • Random bust (Monte Carlo) • Genetic • Branches and borders	• Runs for each classifier separately • Provides a solution for the model training algorithm that is applied	*Advantages* • Providing the best solution • Identifying relationships between features *Limitation* • High computational complexity • Low decision speed • Tendency to retrain in a small training dataset	Cross-validation
Embedding	• Decision trees • Random forest • LASSO • Artificial neural networks • Weighted SVM vectors	• Selects features during model training • Runs for each classifier separately • Provides a solution for the model training algorithm that is applied	*Advantages* • Average computational complexity • Identifying relationships between features • Slight tendency to retrain in a small training dataset *Limitation* • Does not guarantee a better solution • Low zoom	Cross-validation

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Table 2. **Investigation of existing approaches to diagnostic models building for ASTD**

An approach to feature building	Feature selection algorithms	The main characteristics of the approach	Advantages / limitations of the approach	Criteria for the model value
Linear transformations	• Principal Component Method (Karunen-Loeva) • Factor analysis • Discriminant analysis	• Based on internal data properties • Runs once • Performs before applying the model training algorithm • Selects attributes regardless of classifier	*Advantages* • Low computational complexity • High decision speed • Convenience of handling large amounts of data • Does not take into account the relationship between the features *Limitation* • Does not guarantee a better solution when dealing with nonlinear ODs	Validation
Spectral transformations	• Fourier transform • Wavelet transform • Moments	• Based on the intrinsic properties of the signals • Runs once • Performs before applying the model training algorithm • Selects attributes regardless of classifier	*Advantages* • Low computational complexity • High decision speed • Convenience of handling large amounts of data • Good scaling *Limitation* • Does not take into account the relationship between the features • Focuses on smooth signal processing	Validation
Nonlinear transformations	• Kohonen self-organizing maps • Autocoding (neural networks direct distribution) • Convolution neural networks	• Runs for each classifier separately • Provides a solution for the particular model training algorithm that is applied	*Advantages* • Providing the best solution • Identifying relationships between features *Limitation* • High computational complexity • Low decision speed • Tendency to retrain in a small training dataset	Cross-validation

***Source*: compiled by the author**

In order to increase the reliability and noise immunity of the diagnostic procedure, diagnostic models are proposed that combine the features obtained by wavelet transforms $x_c = (c_1,\ldots, c_p)$ of continuous DO models [25] and features obtained from moments of different orders $x_\mu = (\mu_1,\ldots, \mu_r)$ continuous DO models [15].

In view of the above, the paper offers a hybrid method of forming diagnostic models based on the combination of the specified spectral characteristics of nonlinear dynamic DO. The method consists in sequential execution of the following steps (Table 3).

In the work, the effectiveness of the selected set of features was evaluated by the results of the solution of the problem of classification of objects of the examination sample with the help of a decision rule built by one of the algorithms.

Construction of a diagnostic model of a switched reluctance motor. The task of diagnosing switched reluctance motor (SRM) is to build a diagnostic model of the drive based on indirect measurements of the air gap δ between the rotor and the stator of the motor. Direct measurements are unacceptable because they are time consuming and require decommissioning of SRM at the time of inspection.

To estimate the magnitude of the air gap δ between the rotor and the SRM stator, it is proposed in [26] to use data of the side input-output measurements, on the basis of which the model is constructed in the form of multidimensional weight functions (MWF) w_k (τ_1 ,…, τ_k) [27]. A block diagram of the organization of the experiment "input-output" in the problem of diagnosing ARF is shown in Fig. 1. The input signal $x(t)$ (input voltage U_φ) is specified by the diagnostic signals generator DSG, the output signal $y(t)$ (phase current I_φ, at which the air gap δ between the rotor and the stator is measured) is measured by the recording device RD recording device.

Table 3. **Stages of the hybrid method of diagnostic models building based on the combination of spectral characteristics of nonlinear dynamic ODs**

Stage		Description
No.	Name	
1.	Preparation of a discrete training sample	Objective: to obtain a discrete training sample **x** *Input*: models $f_i(t)$, i=1,2,…,m – number of DO models in the training sample *Model*: sampling operator (1) *Output*: training sample **x**
2.	Feature filtering	Objective: to obtain primary diagnostic space *Input*: training sample **x** *Model*: information entropy *Output*: diagnostic features x_j, j=1,2,…,k, k<n, ranked by value
3.	Building a secondary feature space	Objective: to obtain a secondary diagnostic space *Input*: a training sample of the *k* most valuable diagnostic features *Model*: spectral transforms: wavelet transforms $\mathbf{x}_c$ and moments $\mathbf{x}_\mu$ *Output*: Combining spectral features: wavelet transforms and moments $\mathbf{x} = \mathbf{x}_c \cup \mathbf{x}_\mu$
4.	Diagnostic features wrapping	Objective: to build a diagnostic model *Input*: combining spectral features: wavelet transforms and moments $\mathbf{x} = \mathbf{x}_c \cup \mathbf{x}_\mu$ *Output*: a complete mix of spectral characteristics and Bayesian training *Вихід*: diagnostic model
5.	Estimation of parameters of the DO diagnostic model	Objective: to evaluate the quality of the diagnostic model *Input*: examination sample based on feature vector *Model*: expression for validity, error of 1,2 kind, sensuality, specificity *Output*: the value of validity, error of 1.2 kind, sensitivity, specificity

***Source*: compiled by the author**

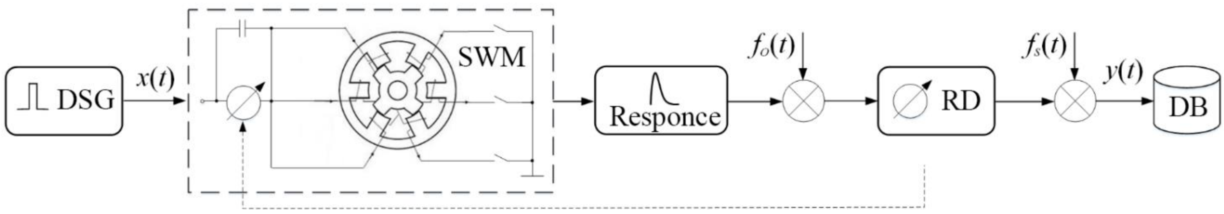

Fig. 1. **A block diagram of the indirect measurements organization in the problem of SRM diagnosing**
***Source*: compiled by the author**

The identification of SRM in the form of MWF is carried out using the simulation model of the engine VREP – 57–005 (rated torque – 0.04 Nm, rated voltage – 24 V, maximum rpm – 4000 rpm), which specifies an implicit description of input-output at a fixed rotor position in the form of a system of equations:

$$\begin{cases} U_{\Phi}=I_{\Phi}R_{\Phi}+\dfrac{d\Psi_{\Phi}}{dt}, \\ \Psi_{\Phi}=f_1(I_{\Phi},\Theta) \end{cases} \qquad (2)$$

where: $U_{\Phi}(t)$ – voltage (input variable); $I_{\Phi}(t)$ – current (measured response of SRM, output variable); R_{Φ} – resistance; Ψ_{Φ} – phase coupling; Θ is the angle of rotor position relative to the stator.

According to [21], on the basis of the simulation model, nonlinear dependences $\psi_{\Phi}(I_{\Phi})$ are obtained for the angle of position of the rotor relatively the stator $\Theta = 30^0$ and the three air gaps between the rotor and the stator: nominal δn = 0.15 mm and δ = 1.3δn and δ = 1.6δn corresponding to the increase by 30 % and 60 % relative to the nominal. The numerical calculation of the dependences (2) is performed on the basis of the FEM field mathematical model.

Analytical expressions for MWF [28–30] of the first $w_1(t)$ order and diagonal cross sections of MWF of the second order $w_2(t,t)$:

$$w_1(t)=e^{-\alpha t},\ w_2(t,t)=\frac{\beta}{\alpha}\left(e^{-2\alpha t}-e^{-\alpha t}\right). \qquad (3)$$

Training sample in the form of first-order MWF $w_1(t)$ (Fig. 2a) and diagonal cross-sections of second-order MWF $w_2(t,t)$ (Fig. 2b) for different values of the air gap δ are obtained for various SRM states and divided into 3 classes (Table 4) by 100 elements in each class: for δϵ [δn, 1.3δn] (normal mode – class A), δϵ (1.3δn, 1.6δn] (fault mode class – B), δ> δn (emergency mode – class C), δn is the nominal value of the air gap δ.

Table 4. **Formation of training sample classes depending on the air gap value δ**

State class	Operating mode	The value of an air gap δ
A	Normal	$\delta\epsilon[\delta_n, 1.3\delta_n]$
B	Fault	$\delta\epsilon(1.3\delta_n, 1.6\delta_n]$
C	Emergency	$\delta>1.6\delta_n$

***Source*: compiled by the author**

In Fig. 3 presents the calculation of the diagnostic value of *I* primary signs of DO – *n* samples of first-order MWF $w_1(t)$ (Fig. 3, left) and diagonal cross-sections of second-order MWF $w_2(t,t)$ (Fig. 3, right). The diagnostic value of the samples was determined as the information entropy $H(x)$ [6] by the expression:

$$H(x)=-\sum_{i=1}^{n} p_i\, log_2 p_i. \qquad (4)$$

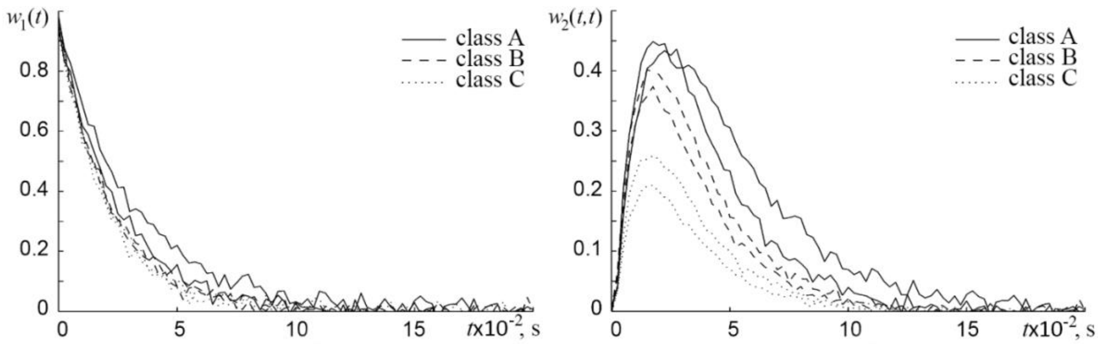

Fig. 2. **On the left – are first-order MWF $w_1(t)$; on the right – are diagonal cross sections of second-order MWF $w_2(t,t)$ at different values of the air gap δ**

***Source*: compiled by the author**

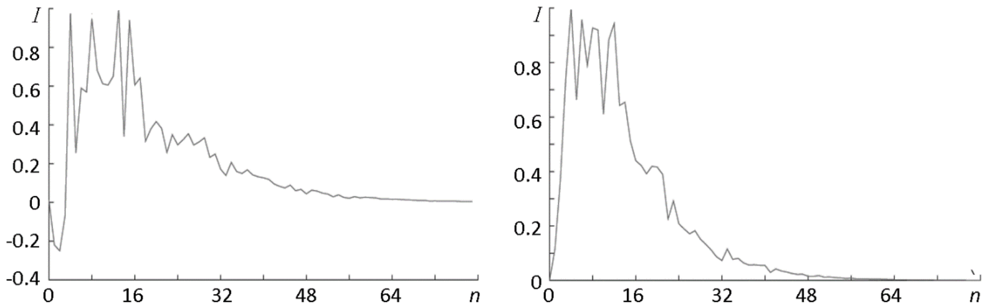

Fig. 3. **Diagnostic value of samples:**
on the left –first-order MWF $w_1(t)$;
on the right – are diagonal cross sections of second order MWF $w_2(t,t)$
***Source*: compiled by the author**

The reliability index P (probability of correct recognition) of the formed spaces of diagnostic signs is investigated: readings $x_k=f(t_k)$, $t_k=k\Delta t$, k=1,10 first-order MWF $w_1(t)$ (diagnostic space $\mathbf{Y}_1$) and diagonal sections second-order MWF $w_2(t,t)$ (diagnostic space $\mathbf{Y}_2$), moments $x_{\mu r}$, r = 0,1,2,3 first-order MWF $w_1(t)$ (diagnostic space $\mathbf{M}_1$) and diagonal cross-sections of MWF of the second order $w_2(t,t)$ (diagnostic space $\mathbf{M}_2$), wavelet transformation x_{ci}, i = 1, ..., 9 first order MWF $w_1(t)$ (diagnostic space $\mathbf{W}_1$) and diagonal sections of second order MWF $w_2(t,t)$ (diagnostic space $\mathbf{W}_2$).

Results of investigations of reliability of diagnostic models depending on various errors of measurement of reaction of system: 1, 3, 5 and 10 % are presented in Table 5 and in Fig. 4.

Diagnostic spaces $\mathbf{Y}_1$, $\mathbf{Y}_2$ have sufficient reliability, which during the interference is significantly reduced. Diagnostic spaces $\mathbf{M}_1$, $\mathbf{M}_2$ and $\mathbf{W}_1$, $\mathbf{W}_2$ make it possible to increase the accuracy of diagnosis, which decreases more slowly than in diagnostic spaces $\mathbf{Y}_1$, $\mathbf{Y}_2$ as the noise level increases.

To improve the accuracy of diagnosis, we consider a model based on the combination of spectral characteristics: moments and wavelet transform signals $x_{\mu r}$, ∪ x_{ci}, r=0,1,2,3, i=1,…,9 (diagnostic space $\mathbf{MW}_1$, $\mathbf{MW}_2$).

The space of the diagnostic oznak $\mathbf{MW}_2$ demonstration of zavadostiykist, nizh inshi rozljanyut expanse: vidliki, moments that wavelet re-creation of the first non-interrupted DO models.

CONCLUSIONS

The article discusses the practical aspects of nonlinear dynamics objects diagnostics taking into account the processes of feature selection and classification for objects of different nature.

In this work has successfully solved the task of improving the availability of diagnostics of non-linear dynamic objects in order to formulate the diagnostic models in the minds of the most detailed description of the problems and the need for further diagnosis.

In order to reach the metadata, a look was made into the methods for formulating the diagnostic models of DO, including non-linear dynamic characteristics.

Table 5. **Accuracy of DO diagnosis, depending on the evaluating model level of interference ε**
***Source*: compiled by the author**

Diagnostic space	Diagnostic features	Interference level ε, %				
		0	***1***	***3***	***5***	***10***
$\mathbf{Y}_1$	x_1, x_2, x_3, x_4	0,993	0,981	0,936	0,885	0,825
$\mathbf{M}_1$	$x_{\mu1}, x_{\mu2}, x_{\mu3}$	0,994	0,988	0,980	0,954	0,927
$\mathbf{W}_1$	$x_{c1}, x_{c2}, x_{c3}, x_{c4}$	1	0,995	0,990	0,973	0,946
$\mathbf{MW}_1$	$x_{\mu2}, x_{c2}, x_{c3}, x_{c4}$	1	1	0.990	0,981	0,963
$\mathbf{Y}_2$	x_1, x_2, x_3, x_4	1	0,998	0,995	0,987	0,979
$\mathbf{M}_2$	$x_{\mu1}, x_{\mu2}, x_{\mu3}$	1	0,999	0,997	0,994	0,993
$\mathbf{W}_2$	$x_{c1}, x_{c2}, x_{c3}, x_{c4}$	1	1	0,999	0,996	0,995
$\mathbf{MW}_2$	$x_{\mu2}, x_{c2}, x_{c3}, x_{c4}$	1	1	1	1	1

***Source*: compiled by the author**

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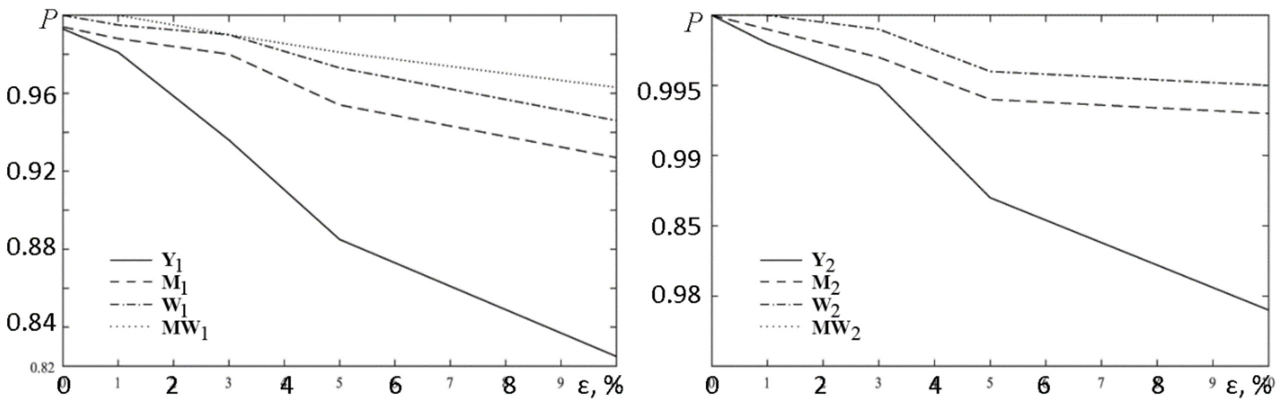

Fig. 4. **Diagnostic value of models:**
on the left – counts of first-order MWF $w_1(t)$ (Y_1), its moments (M_1), wavelet transform (W_1), moment combination and wavelet transform (MW_1);
on the right – are the readings of diagonal cross sections of second-order MWF $w_2(t,t)$ (Y_2), its moments (M_2): wavelet transform (W_2), moment combination and wavelet transform (MW_2)
***Source*: compiled by the author**

It has been established that the methods of filtering are more efficiently enumerated. Methods of clipping and vbudovuvannya oznak slid vikoristovuvati, if you need to know the diagnosis simple, adaptations to the singing algorithm to start. Gibridny pidkhid vikoristovє overtaking rozgljanyutih methods.

The analysis of basic methods and the remaining trends in the field of encouraging diagnostic models allowed the problem of increased reliability and diagnosis of non-linear models in the first place to be fully understood. In such minds, the method of filing is not secure, the task of diagnosis is determined, and the method of clipping is the most important, because it is important to assess the complexity of tasks (damn it).

So, having discredited the furthest development, the method of diagnosis of non-linear dynamic objects with a whip of the last consecutive methods of filtering and chipping. At the first this method, we'll have to vibrate the most significant number of signs using the filter method for the next little sign. On the other hand, it's healthy to vibrate optimally from the point of view of reliability and diagnostics of signs based on a combination of spectral characteristics by the method of clipping.

The suggested method has been tested on real-life task of diagnosing a non-linear dynamic object – a electric motor. The method is demonstrate more independence of the accessibility indicator then existing methods of the diagnostic feature space biulding: the samples, the moment and the coefficients of wavelet transformations of the primary diagnostic models.

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ФОРМУВАННЯ ДІАГНОСТИЧНИХ МОДЕЛЕЙ НА ОСНОВІ КОМБІНУВАННЯ СПЕКТРАЛЬНИХ ХАРАКТЕРИСТИК НЕЛІНІЙНИХ ДИНАМІЧНИХ ОБ’ЄКТІВ

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АНОТАЦІЯ

В роботі вирішується задача побудови діагностичних моделей для об'єктів нелінійної динаміки. Розглянуто причини збільшення розмірності опису сучасних об'єктів діагностування і пов'язані з цим проблеми використання існуючих методів діагностики. Метою роботи є підвищення достовірності діагностування нелінійних динамічних об’єктів шляхом формування діагностичних моделей в умовах збільшення розмірності опису об'єктів діагностування для створення ефективних інструментальних засобів автоматизованих систем технічного діагностування об´єктів різної природи. Наведено широкий огляд і класифікацію методів зниження розмірності простору діагностичних ознак, в тому числі, для нелінійних динамічних об'єктів з неперервними характеристиками та невідомою структурою, які можна розглядати як «чорну скриньку». Запропоновано метод формування діагностичних моделей нелінійних динамічних об'єктів на основі комбінування спектральних характеристик, отриманих в результаті перетворень неперервних моделей: коефіцієнтів вейвлет-перетворень та моментів різних порядків досліджуваних моделей. Запропоновано сімейство діагностичних моделей у вигляді комбінацій спектральних характеристик динамічних об’єктів зі слабкою нелінійністю. Запропоновано гібридний метод формування діагностичних моделей у вигляді комбінацій спектральних характеристик. Метод складається з послідовного застосування фільтрації ознак для формування первинного простору діагностичних ознак, побудови простору вторинних ознак за допомогою спектральних перетворень та побудови діагностичної моделі методом обертання з використанням методу повного перебору вторинних ознак. Наведено покроковий алгоритм формування діагностичних моделей за допомогою запропонованого гібридного методу. Запропонований метод апробовано на реальній задачі діагностування нелінійного динамічного об'єкта - електричного двигуна. Первинна діагностична модель електродвигуна отримана на основі непрямих вимірювань повітряного зазору між ротором і статором двигуна. Діагностичні моделі, побудовані поєднанням спектральних характеристик безперервних моделей. Запропоновано сімейство діагностичних моделей електричного двигуна. Метод демонструє більшу завадостійкість показника достовірності, ніж існуючі методи побудови просторів діагностичних ознак: відліків, момент та коефіцієнтів вейвлет перетворень первинних діагностичних моделей.

Ключові слова: нелінійні динамічні об’єкти; діагностичні моделі; редукція моделей; спектральні перетворення

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ФОРМИРОВАНИЕ ДИАГНОСТИЧЕСКОЙ МОДЕЛИ НА ОСНОВЕ КОМБИНИРОВАНИЯ СПЕКТРАЛЬНЫХ ХАРАКТЕРИСТИК НЕЛИНЕЙНЫХ ДИНАМИЧЕСКИХ ОБЪЕКТОВ

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АННОТАЦИЯ

В работе решается задача построения диагностических моделей для объектов нелинейной динамики. Рассмотрены причины увеличения размерности описания современных объектов диагностирования и связанные с этим проблемы использования существующих методов диагностики. Целью работы является повышение достоверности диагностирования нелинейных динамических объектов путем формирования диагностических моделей в условиях увеличения размерности описания объектов диагностирования для создания эффективных инструментальных средств автоматизированных систем технического диагностирования объектов различной природы. Приведены широкий обзор и классификацию методов снижения размерности пространства диагностических признаков, в том числе, для нелинейных динамических объектов с непрерывными характеристиками и неизвестной структурой, которые можно рассматривать как «черный ящик». Предложен метод формирования диагностических моделей нелинейных динамических объектов на основе комбинирования спектральных характеристик, полученных в результате преобразований непрерывных моделей: коэффициентов вейвлет-преобразований и моментов различных порядков исследуемых моделей. Предложено семейство диагностических моделей в виде комбинаций спектральных характеристик динамических объектов со слабой нелинейностью. Предложен гибридный метод формирования диагностических моделей в виде комбинаций спектральных характеристик. Метод состоит из последовательного применения фильтрации признаков для формирования первичного пространства диагностических признаков, построения пространства вторичных признаков с помощью спектральных преобразований и построения диагностической модели методом вращения с использованием метода полного перебора вторичных признаков. Приведены пошаговый алгоритм формирования диагностических моделей с помощью предложенного гибридного метода. Предложенный метод апробирован на реальной задаче диагностирования нелинейного динамического объекта – электрического двигателя. Первичная диагностическая модель электродвигателя получена на основе косвенных измерений воздушного зазора между ротором и статором двигателя. Диагностические модели, построены сочетанием спектральных характеристик непрерывных моделей. Предложено семейство диагностических моделей электрического двигателя. Метод демонстрирует большую помехоустойчивость показателя достоверности, чем существующие методы построения пространств диагностических признаков: отсчетов, момент и коэффициентов вейвлет-преобразований первичных диагностических моделей.

Ключевые слова: нелинейные динамические объекты; диагностические модели; редукция моделей; спектральные преобразования

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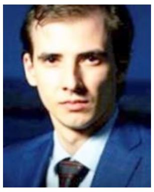

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