Method for Construction the Diagnostic Features Space of Switched Reluctance Motors Based on Integral Dynamic Models

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Abstract. The work is devoted to the problem of construction the diagnostic models for the nonlinear dynamic objects. The aim of the work is to improve the reliability and fast operation in diagnosis of the states of electrical motors of under conditions of an a priori uncertainty. The a priori uncertainty results from an insufficient study of the processes, which occur in the objects of diagnosis due to the operation in a wide range of external conditions and the presence of a great amount of disturbing effects along with environmental interferences. This aim is achieved by the development of the technical diagnosis method based on the information models of the nonlinear dynamic objects of diagnosis, which are obtained using the nonparametric identification procedure. As the information models of diagnostic objects, the integral nonparametric dynamic models based on multidimensional weight functions are considered. The most significant results consist in obtaining the method with a further development in construction of a space of diagnostic features of the nonlinear dynamic objects based on the correlation analysis as a stage of the features' filtration. The latter ensures the maximum diagnostic reliability. Significance of the obtained results: the application of the proposed method allows both high reliability of the object diagnosis under the priory uncertainty, and improvement of the diagnostic procedure fast operation owing to the feature filtration. The proposed method was tested using the data of the diagnosis of the switched reluctance motors.

***Keywords*:** nonlinear dynamic objects, diagnostic models, model reduction, feature selection, correlation analysis.
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Metodă pentru construirea spațiului caracteristicilor de diagnostic ale motoarelor cu jet de supapă pe baza modelelor dinamice integrale

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***Rezumat*.** Scopul lucrării este de a spori fiabilitatea și viteza diagnosticării stărilor motoarelor electrice ale diferitelor obiecte energetice în condiții de incertitudine a priori. Incertitudinea a priori este cauzată de cunoașterea insuficientă a proceselor care apar în obiectele de diagnosticare din cauza funcționării într-o gamă largă de condiții externe și prezenței unui număr mare de influențe perturbatoare și perturbări ale mediului. Acest obiectiv este atins prin dezvoltarea unei metode de diagnosticare tehnică bazată pe modele de informații ale obiectelor dinamice neliniare de diagnostic, obținute utilizând procedura de identificare nonparametrică. În calitate de modele informaționale ale obiectelor pentru diagnosticare se propun modelele dinamice integrale nonparametrice bazate pe funcții de pondere multidimensionale, care descriu simultan proprietățile neliniare și inerțiale ale unui obiect, capabile să ia în considerare defecțiunile cauzate de ambele modificări ale parametrilor și structurii unui obiect, precum și de a oferi confort în testare și diagnosticarea funcțională. Cele mai importante rezultate: metoda de construire a spațiului caracteristicilor de diagnostic ale obiectelor dinamice neliniare pe baza modelelor informaționale sub formă de funcții de pondere multidimensionale a fost dezvoltată în continuare prin utilizarea analizei de corelație cu un factor și multivariabil ca etapă de filtrare a caracteristicilor cu enumerarea ulterioară a combinațiilor de caracteristici, care asigură o credibilitatea maxima de diagnosticare. Semnificația rezultatelor obținute: utilizarea metodei propuse permite în același timp asigurarea unei ctredibilității ridicate a diagnosticării obiectelor în condiții de incertitudine a priori datorită utilizării modelelor de informații primare bazate pe funcții de pondere multidimensionale și creșterea vitezei procedurii de diagnostic datorită caracteristicilor de filtrare bazate pe analiza corelației spațiului de diagnostic.

***Cuvinte-cheie*:** obiecte dinamice neliniare, modele de diagnostic, reducerea modelului, selectarea caracteristicilor, analiza corelației.

Метод построения пространства диагностических признаков вентильно-реактивных двигателей на основе интегральных динамических моделей

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Аннотация. В работе решается задача построения диагностических моделей для нелинейных динамических объектов. Целью работы является повышение достоверности и быстродействия диагностирования состояний электродвигателей различных энергетических объектов в условиях априорной неопределенности. Априорная неопределенность вызвана недостаточной изученностью процессов, протекающих в объектах диагностирования вследствие эксплуатации в широком диапазоне внешних условий и наличия большого количества возмущающих воздействий и помех окружающей среды. Поставленная цель достигается путем развития метода технической диагностики на основе информационных моделей нелинейных динамических объектов диагностирования, полученных при помощи процедуры непараметрической идентификации. В качестве информационных моделей объектов диагностирования рассматриваются интегральные непараметрические динамические модели на основе многомерных весовых функций, одновременно описывающие нелинейные и инерционные свойства объекта, способные учитывать неисправности, вызванные как изменением параметров, так и структуры объекта, а также обеспечивающие удобство при тестовом и функциональном диагностировании. Наиболее существенные результаты: получил дальнейшее развитие метод построения пространства диагностических признаков нелинейных динамических объектов на основе информационных моделей в виде многомерных весовых функций путем применения однофакторного и многофакторного корреляционного анализа в качестве этапа фильтрации признаков с последующим перебором сочетаний признаков, что обеспечивает максимальную достоверность диагностирования. Значимость полученных результатов: применение предложенного метода позволяет одновременно обеспечить высокую достоверность диагностирования объектов в условиях априорной неопределенности благодаря использованию первичных информационных моделей на основе многомерных весовых функций и повысить быстродействие диагностической процедуры благодаря фильтрации признаков на основе корреляционного анализа диагностического пространства. Предложенный метод апробирован на данных задачи диагностирования вентильно-реактивного двигателя. Пример демонстрирует сокращение вычислительной сложности при построении диагностической модели по сравнению с методом на основе отсчетов с равномерным шагом при обеспечении заданной достоверности диагностирования.

Ключевые слова: нелинейные динамические объекты, диагностические модели, редукция моделей, отбор признаков, корреляционный анализ.

INTRODUCTION

With an increase in the complexity of modern objects of control and the conditions of their operation in different branches of engineering, industry or transport, the role is intensified of the automatized systems of technical diagnosis (ASTD) for accident prevention, for estimation of the articles' quality, minimization of the technical services expenses [1—3].

In conditions of the increased practical interest, the application problems of diagnosis of complex objects become widespread, particularly, of those based on nonelinear inertial objects, including the objects with continuous characteristics and unknown structure, which can be referred to as the "black box" [4—6].

Typical examples of the objects like these are the electrical motors. The application of the electrical motors in power engineering, industry, and at transport is conditioned by their high efficiency and, what is particularly important at present, by their ecological compatibility. Therefore, nowadays, the improvement of their operational characteristics, reliability and a service life are of primary importance.

The most significant problem of the technical diagnostics (TD) is timely and reliable determination of the technical state of the electrical motors of various power objects (railway traction engines, motor vehicles, lifting and transporting equipment, etc.) [7, 8].

The objects like these are often accompanied by the a priory uncertainty, which results from the insufficient study of the processes that occur in the diagnosis objects (DO), as well as from the operation in the wide range of the external conditions, the presence of a good many disturbing actions and the environmental interferences [9, 10].

At present, the technical diagnostics suggests that defects change only the parameters of the DO model, which at diagnosis are evaluated using the methods of the parametric identification [11—13].

However, the defects and degradation processes in the objects can often change not only the DO model parameters, but its structure as well [14—16].

Therefore, the diagnosis oriented to the object model restoration (model diagnostic) is developed more extensively, when the use of the methods of nonparametric identification is conditioned in diagnosis for the construction of the DO information model on the basis of the "input-output" experimental data [15—18].

The application of the existing model diagnostics methods is limited by their insufficient efficiency and versatility. In [19, 20], for the purpose of diagnosis, the linear dynamic models are used. In [21, 22], the models are applied based on the accounting of the effects of nonlinearity, which take into account only the information on the properties of the DO static characteristics. Real objects, as a rule, are characterized, at the same time, both by nonlinear and dynamic properties.

Unlike [15—18, 23—25], the present work, as the information DO models with an uncertain structure, contains the integral nonparametric dynamic models based on the multidimensional weight functions (MDWF), which were obtained using the 'input-output' experimental data.

The major advantages of the use of these models are the following: the ability to simultaneously and briefly describe the nonlinear and inertial DO properties, which ensures high reliability of the diagnosis [23, 26]; the ability to take into account the malfunctions, which resulted both from the changes in the DO parameters and structure [26]; and the test and functional diagnosis convenience [25].

The work is aimed at improvement the reliability and fast-operation diagnosis of the states of the electric motors of different power objects under the a priori uncertainty by means of development of the model diagnostics method based on the DO nonparametric identification in the form of the integral dynamic models.

I. Integral nonparametric dynamic models and identification of diagnosis objects

For a wide class of the nonlinear dynamic systems, the dependence between the action $x(t)$ and reaction $y(t)$ in an explicit form can be presented as a functional integro-power series of Volterra [23, 25, 26].

The 'input-output' ratio for the continuous nonlinear dynamic system with the unknown structure (of the 'black box' type) at one input and one output can be presented as the Volterra series:

$$\begin{aligned} y(t) &= w_0(t) + \int_0^t w_1(\tau)x(t-\tau)d\tau + \\ &+ \int_0^t\int_0^t w_2(\tau_1,\tau_2)x(t-\tau_1)x(t-\tau_2)d\tau_1 d\tau_2 + \\ &+ \int_0^t\int_0^t\int_0^t w_3(\tau_1,\tau_2,\tau_3)x(t-\tau_1)x(t-\tau_2)x(t-\tau_3)\times \\ &\times d\tau_1 d\tau_2 d\tau_3 + \ldots = w_0(t) + \sum_{n=1}^{\infty} y_n(t), \end{aligned} \tag{1}$$

where $w_n(\tau_1,...,\tau_n)$ is the MDWF of the *n-th* order (n=1, 2, 3,…), the symmetric function with respect to the real variables $\tau_1,\ldots,\tau_n$; $w_0(t)$ is the free series term, at the zero initial conditions $w_0(t)\equiv 0$; and t is the current time.

The model construction of the nonlinear dynamic DO in the form of the MDWF consists in selection of the forms of the testing $x(t)$ and the algorithm development, which makes it possible, according to the measured $y(t)$ reactions, to reveal the partial components $y_n(t)$ and on their bases determine the MDWF $w_n(\tau_1,...,\tau_n)$, n=1, 2, ... the n-dimensional transfer functions.

The disadvantage of this model is a large volume of the identification data, which reduces the fast-operation of the ASTD adjustment.

The volume reduction of the primary identification information using more compact models (e.g., convolution integrals) allows the ASTD fast-operation increase, however, it decreases the diagnosis reliability. Thus, the contradiction arises between the reliability of the TD and the ASTD adjustment fast-operation, when using the integral nonparametric dynamic models.

The contradiction can be settled by the development of a new secondary identification method — the construction of a space of diagnostic features $\mathbf{x}$ with a substantially smaller dimension of the diagnostic information.

II. Construction of diagnostic features' space based on methods of filtration

The efficient method for presenting the information models as a vector of features $\mathbf{x}$ is a parametrization of continuous DO models $y(t)$: $\{w_n(\tau_1,\ldots,\tau_n)\}_{n=1,2,\ldots,N} \Rightarrow \mathbf{x}=(x_1,\ldots,x_k)'$, where N is the order of the information model; k is the dimension of the diagnostic model; slant is the vector conjugation.

A vector of diagnostic features can be obtained by means of a certain preliminary transformation of the form $T_j : C[a,b] \to R^n$, $(j = 1,\ldots,n)$: $x_j = T_j(f(\tau_1,\ldots,\tau_k))$, where $C[a,b]$ is the space of real continuous functions $f(t)$, preset at section $[a,b]$; a, b are certain real numbers.

As operator T_j, the orthogonal expansions can be used [27] and spectral transformations [14, 15] of continuous models into vectors of coefficients of the basis functions.

In practice, it is common to use as T_j, the operator of discretization of a continuous model:

$$x_j = w_n(t_j), \tag{2}$$

where $t_j = j\Delta t$ (Δt is the discretization step).

Modern subsystems of the information registration, which are included in the ASTD composition are able to perform thousands DO responses' measurements per second that ensures the primary diagnostic data integrity. In this case, the measurements results are accompanied by the presence of a plurality of extra data. Moreover, it is obvious that validity of different sections of the DO measured responses is different for the diagnostic procedure.

As is shown in [28, 29], the most valid sites of the DO responses are, as a rule, those that carry the highest energy of a signal. Taking into account all the aforementioned, the use of signal discretization for the formation of the space of the diagnostic features is inefficient.

During the work with the continuous DO characteristics in construction the diagnostic features' space, the most efficient can be the correlation methods of the filtration of the information models' readouts [29—31].

The diagnostic models' formation based on filtration of the features consists in those features' ranking with the application of the statistical methods of estimation the correlation between each of the input and purpose-oriented alternative [28—30]. The latter methods yield fast and efficient results, particularly on processing large data volumes.

There are several types of the correlation methods of estimation the diagnostic validity of features, depending on the data type of both input and output variables, either numerical or categorical data.

The type of a response variable indicates usually the type of the modeling problem. Thus, the numerical output variable indicates the problem of the predictive modelling with regression, while the categorical output variable is indicative of the problem of predictive modelling of classification.

In the diagnostic problems of continuous DO, a case of numerical and categorical inputs is considered. Here, to estimate the correlation between the intergroup and intragroup variability the Fisher F-criterion is used:

$$I = \frac{\sum_{i=1}^{n_j}\left(x_{i,j} - M^2\right)/P-1}{\sum_{i=1}^{n_j}\left(x_{i,j} - M_j^{\,2}\right)/L-J},$$

where M is the mathematic expectation of the feature; L is the volume of the complete sample; and P is the number of classes.

This work offers the method for construction of the diagnostic features' space based on continuous information models in the form of the MDWF followed by their discretization and filtration of the features based on the evaluation of their correlation.

III. Method for construction the diagnostic features' space based on integral dynamic models

The offered method for construction the diagnostic features' space based on the integral dynamic models reduces to the identification of the informative MDWF model, according to the data of the 'input-output' experiment. Based on the discrete samples of the obtained continuous models, the features' space is constructed. In the space obtained by filtration of the features based on evaluation of their correlation, the diagnostic models are constructed.

The stages of the method for the construction of the diagnostic features' space based on the integral dynamic models are shown in Table 1. The development of this method consists in addition of stages N3 and N4 to the known procedure of the model diagnosis.

IV. Construction of diagnostic features' space of switched reluctance motor

Approbation of the method for the construction of the diagnostic features' space based on the integral dynamic models is performed by the example of the switched reluctance motor (SRM), which is the continuous object with nonlinear dynamic characteristics.

In the process of a long-term operation of the electromotor (due to the friction of a rotor against the air), the air gap (AG) between the rotor and stator (Fig. 1) increases. Upon the AG increase, the energy indices decrease. i.e., the energy is transformed with high losses.

Table 1

Stages of method for construction of diagnostic features' space based on integral dynamic models.

Stage №	Stage Name	Description
1.	DO identification (construction of information model)	*Aim*: obtainment of DO model in the form of MDWF. *Input*: test signal $x(t)$ *Model*: Volterra series (1) *Output*: MDWF based on 'input-output' experimental data
2.	Information model discretization	*Aim*: obtainment of DO information model in discrete form *Input*: MDWF $w_n(\tau_1,...,\tau_n)$ *Model*: discretization operator (2) *Output*: vector of features **x**
3.	Features' evaluation	*Aim*: to calculate validity of each feature for TD problem *Input*: vector of features **x** *Model*: F-criterion of Fisher (3) *Output*: vector of features $\mathbf{x}^1$, ranked according to validity index *I*
4.	Features' filtration	*Aim*: to obtain diagnostic features' space *Input*: vector of ranked features **x** *Model*: $\mathbf{x}^2=(x_1,\dots,x_p)'\in\mathbf{x}$, $p<n$ *Output*: diagnostic features' space $\mathbf{x}^2=\left(x_1,\dots,x_p\right)'$ with maximum indices of validity *I*

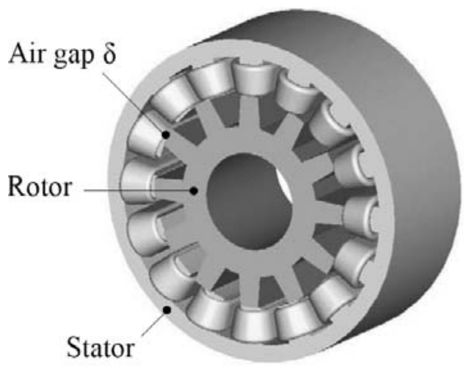


Fig. 1. Air-gap δ between SRM rotor and stator.

In this context, during the SRM operation, it is necessary to control periodically the AG value. The direct measurements are undesirable, since they are time-consuming and need the SRM removal out of the operation for the time of control, which is prohibitive for the most of the energy objects in the mode of functioning.

The SRM diagnostic problem consists in the construction of the electromotor diagnostic model according to the data of the indirect measurements of the air-gap between its rotor and stator.

This problem is complicated by the following: the motor itself is an object with nonlinear dynamic characteristics; the motor operates in a wide range of external conditions in the presence of a great number of disturbing effects and environmental interferences; in conditions of the operation it is necessary to ensure the reliable and operative diagnosis of the motor state.

Thus, the problem of the functional diagnostics of the electromotor AG between the rotor and stator, according to the data of the indirect measurements (indirect methods), based on the 'input-output' information models has an important practical meaning. The structural scheme of organization of the 'input-output' experiment in the SRM diagnostic problem is shown in Fig. 2.

The input signal $x(t)$ is preset by the generator of the diagnostic signals (GDS), the output signal $y(t)$ is measured by the registration device (RD) and is written into the database (DB); $f_o(t)$ and $f_s(t)$ are the environmental and detector interferences.

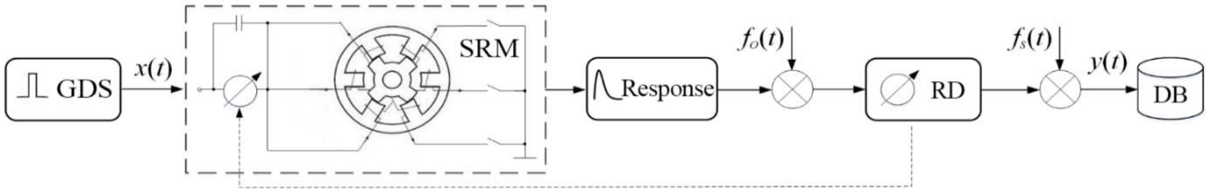


Fig. 2. Structural scheme of organization of experiment 'input-output' in SRM diagnostic problem.

The SRM diagnostic procedure is performed in the order listed in Table 1.

DO identification.

For the diagnostic purposes, it is advisable to use the mathematic model of the motor, which presets the abstract description of the motor of the 'input-output' type in the form of the equation system at a fixed position of the rotor [32]:

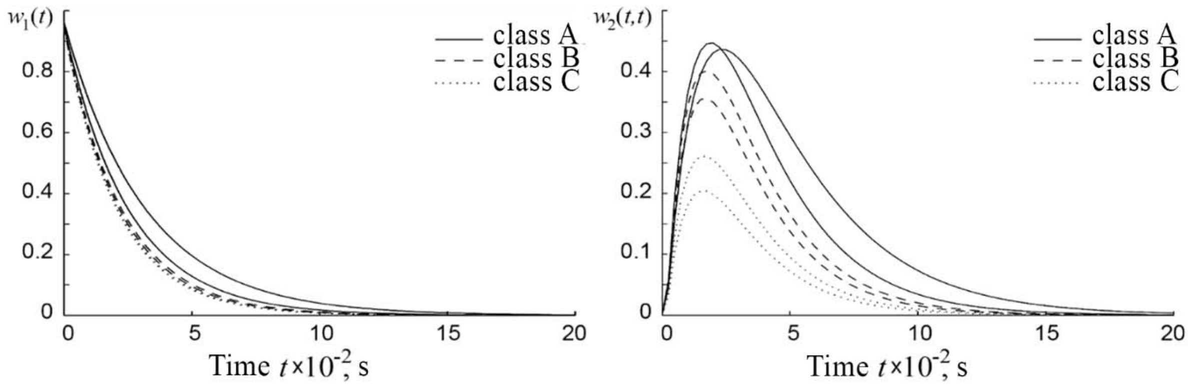
$$\begin{cases} U_\Phi = I_\Phi R_\Phi + \dfrac{d\Psi_\Phi}{dt} \\ \Psi_\Phi = f_I\left(I_\Phi, \Theta\right) \end{cases} \qquad (4)$$

where $U_\Phi(t)$ is the voltage (input variable); $I_\Phi(t)$ is the current (the SRM measured response, the output variable); R_Φ is the resistance, Ψ_Φ is the magnetic flux linkage of the phase; and Θ is the angle of position of the rotor with regard to position of stator.

The analytic expressions for the MDWF of the first order and diagonal sections of the MDWF of the second order:

$$w_1(t) = e^{-\alpha t}, w_2(t,t) = \frac{\beta}{\alpha}\left(e^{-2\alpha t} - e^{-2\alpha t}\right) \qquad (5)$$

Teaching full sample in the form of the MDWF of the first order $w_1(t)$ (Fig. 3a) and diagonal sections of the MDWF of the second order $w_2(t,t)$ (Fig. 3b) at different δ values of the AG is obtained for different SRM states and is divided into 3 classes, 100 elements each: for $\delta \in [\delta_n, 1.3\delta_n]$ (normal mode is class A), $\delta \in (1.3\delta_n, 1.6\delta_n]$ (malfunction mode is class B), and $\delta > \delta_n$ (emergency mode is class C).



a b

Fig. 3. a – MDWF of the first order $w_1(t)$; b -- diagonal section of MDWF of the second order $w_2(t,t)$ for classes A, B, and C.

Discretization of information model.

To carry out the experimental studies the MDWF and their sections readouts were used, which were obtained with a step of Δt =2.5 μs.

The space of diagnostic features $\mathbf{x} = (x_1, \dots, x_l)'$ was constructed in the form of the readout samples of the MDWF diagonal sections $w_k(t - \tau_1, \dots, t - \tau_k)$ of the order of k = 1, 2 with dimension of l=81 readout.

Features' evaluation.

Calculation of diagnostic validity I of the DO primary features: the MDWF readouts of the first order $w_1(t)$ (Fig. 4a) and the MDWF diagonal sections of the second order $w_2(t,t)$ (Fig. 4b) is performed using criterion (2).

As a result, the vector of features $\mathbf{x^1} = (x_1, \dots, x_1)'$ is obtained, which are ranked according to the index of validity *I*.

Features' filtration.

Out of the elements of vector of the diagnostic features $\mathbf{x}^2 = (x_1, \ldots, x_p)'$ is formed by the features' filtration with maximum indices of validity I. The dimension p of space $\mathbf{x}^2$ is selected so as to ensure the preset reliability of diagnosis. In this work, the reliability is evaluated according to the solution results of the classification problem of the objects of the examination sample using the method for a maximum credibility [28].

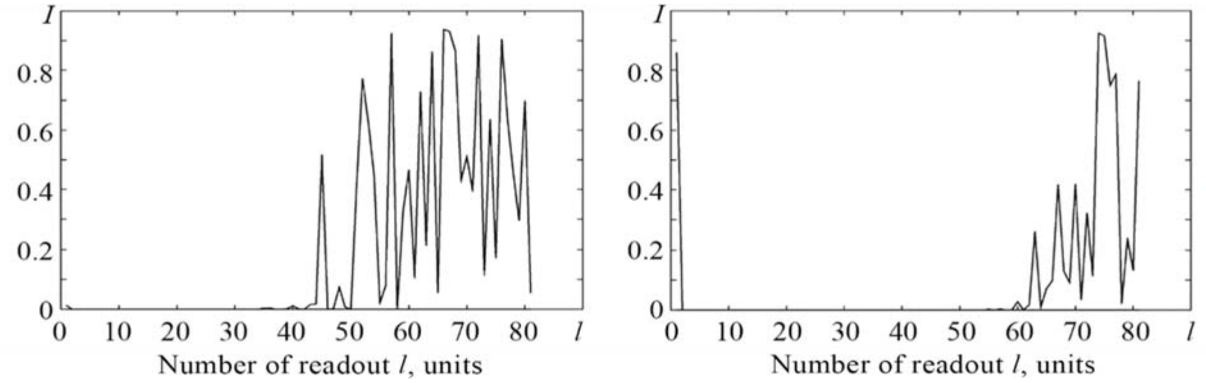


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Fig. 4. Diagnostic validity I of readouts according to criterion (3): a – MDWF of the first order $w_1(t)$; b – diagonal section of MDWF of the second order $w_2(t,t)$.

In this problem at p=5, the SRM diagnostic model, which was constructed using the filtration features $\mathbf{x}^1$ based on correlation, looks as follows $\mathbf{x}^2 = (x_3, x_9, x_{15}, x_{21}, x_{27})$ and ensures the preset level of reliability of diagnostics P=0.99. For comparison, the validity of each feature I of space $\mathbf{x}$ was determined by evaluation the reliability of diagnosis P for each MDWF readout of the first order $w_1(t)$ (Fig. 5a) and the MDWF diagonal sections of the second order $w_2(t,t)$ (Fig. 5b).

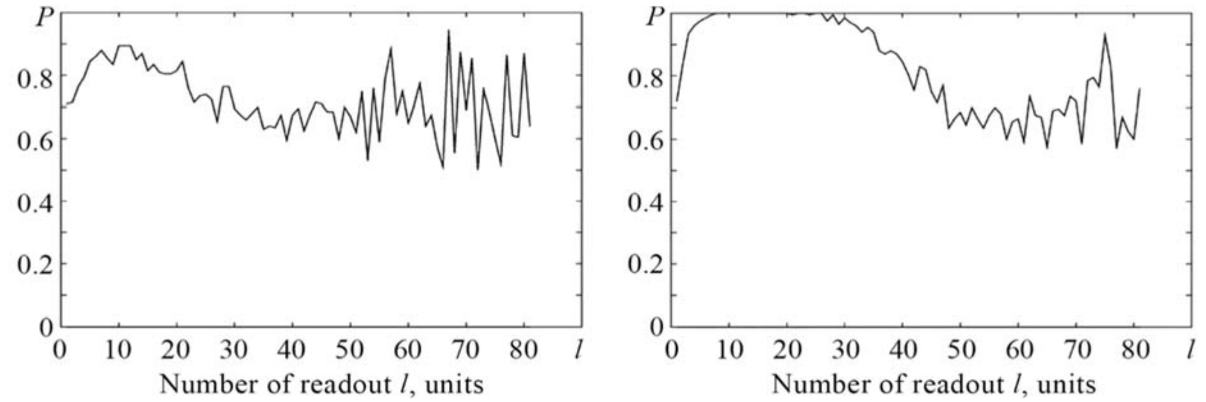

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Fig. 5. Reliability of P readouts: a – MDWF of the first order $w_1(t)$; b – diagonal section of MDWF of the second order $w_2(t,t)$.

As a result of comparison the validity of readouts of the corresponding MDWF models (Figs. 4, 5), it is seen that the diagnostic features obtained by filtration based on correlation, coincide considerably with those selected in accordance to the classification results of the objects of the examination samples, using the decision rule, constructed by the method for the maximum credibility. The calculation complexity in obtaining the result by filtration based on correlation is by 6–8 times lower, than that obtained by the results of classification.

To estimate the diagnostic validity of the features combined with other features, the study was performed using the multifactorial correlation analysis. Figure 6 shows the calculation of the diagnostic validity I of a pairwise combinations of the DO primary features – the MDWF readouts of the first order $w_1(t)$ (Fig. 6a) and those of the

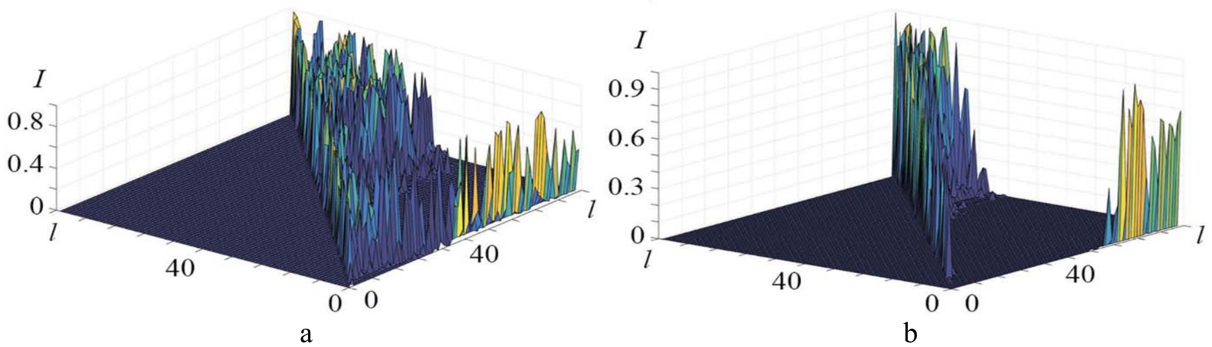

Fig. 6. Diagnostic validity I of pairwise combinations according to criterion (3): a – MDWF of the first order $w_1(t)$; b – diagonal section of MDWF of the second order $w_2(t,t)$.

MDWF diagonal sections of the second order $w_2(t,t)$ (Fig. 6b). Here, the most valid combinations of the diagnostic features are relevant to the minimal values of criterion (3).

For comparison, the validity of the pairwise combinations of the features of space **x** was estimated as reliability of *P* diagnosis for the readouts of the MDWF of the first order $w_1(t)$ (Fig. 7a) and the MDWF diagonal sections of the second order $w_2(t,t)$ (Fig. 7b).

From Figs. 6, 7, it is seen that the combinations of the diagnostic features, which were obtained by the multifactorial correlation analysis, coincide to a high degree with the combinations of the features that were selected according to the objects' classification results using the method of maximal credibility. Moreover, the calculation complexity of obtaining the result by the multifactorial discriminant analysis at the pairwise combination of the features is by 10 – 12 times less, than that according to the results of the classification problem solution.

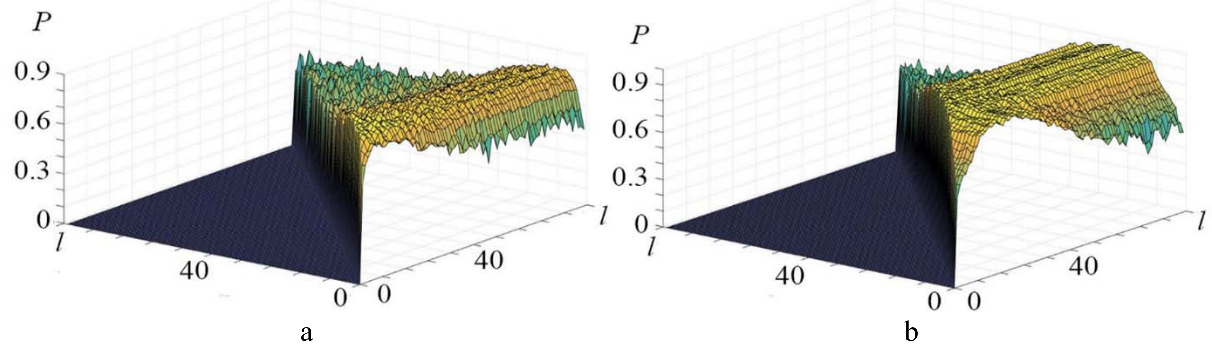

Fig. 7. Reliability of P readouts of pairwise combinations: a – MDWF of the first order $w_1(t)$; b – diagonal section of MDWF of the second order $w_2(t,t)$.

CONCLUSIONS

This work tackles the problem of improvement the reliability and fast-operation of the diagnostics of the electric motors states of different energy objects under the a priori uncertainty by developing the method of the model diagnostics based on the nonparametric identification of the objects in the form of the integral dynamic models.

As the information models of the diagnostic objects, the authors consider the nonparametric models based on the multidimensional weight functions that simultaneously describe the nonlinear and dynamic properties of the object, which are able to consider the malfunctions caused both by the change in parameters and in the object structure. That is particularly convenient at the test and functional diagnostics. The method was further developed that was used for the construction of the diagnostic features' space of nonlinear dynamic objects based on information models in the form of the multidimensional weight functions by the use of the single- and multi-factorial correlation analysis as a stage of the features' filtration with a following selection of the features' combinations to ensure the diagnosis maximum reliability on the basis of the integral dynamic object models. The application of this approach makes it possible to ensure simultaneously a high reliability of the object diagnostics under the a priori uncertainty due to the use of the primary information models based on the multidimensional weight functions and fast-operation of the diagnostic procedure owing to the filtration based on the correlation analysis of the features. A stepwise algorithm of the method is presented with the input and output information along with the data models used at each stage.

The proposed method is approbated on the data of the diagnostic problem of the nonlinear dynamic object, namely, a switched reluctance motor. This example exhibits the reduction in the calculation complexity at the diagnostic model construction compared to the method based on the readouts with a uniform step by 6–12 times, provided the diagnostic reliability is 0.99.

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