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REGRESSION ANALYSIS OF THE PERFORMANCE OF ASYNCHRONOUS ELECTRIC MOTORS ON THE BASIS OF SUPPORT VECTOR MACHINE (SVM)

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Abstract: The subject of the article is relevant, since the proposed method for performing a regression analysis of the operation of asynchronous motors does not have special requirements to the accuracy of measuring the quantities used in the regression analysis and to the volume of a training sample, so it can be used in modern embedded diagnostic systems.

The research methods are based on the use of the support vector machine applied in the regression representation. In this approach, the parameters of a regression model are determined by solving a quadratic programming problem having only one solution. To determine the values of the parameters used to train the model, the general theory of transients in electric machines, methods of mathematical modeling, computational mathematics and methods for determining the symmetric components of generalized vectors are used in the paper.

The regression model based on the support vector machine is used to determine the number of damaged rods of the short-circuited rotor of the asynchronous motor. The efficiency of the model has been confirmed by experimental studies. It has been established that a regression model with the radial basis kernel function has the least value of the mean square deviation. Thus, in cases where a regression relation between controlled coordinates must be used, the use of machine learning methods based on the vector space model whose purpose is to find dividing surfaces between classes located as far as possible from all points of the training set has considerable prospects.

Key words: regression analysis, asynchronous motor, support vector machine, kernel function, short-circuited rotor, diagnostics

1. Introduction

Currently, along with the renewal of the park of electric motors (using motors with increased structural reliability) research is carried out to reveal the possibilities for increasing the duration of the performance of motors being used.

It is aimed at shortening the time of carrying out preventive and restoration works, increasing the operational reliability of electric motors, further creating and using an automated operation management system whose main task will be to support the performance of asynchronous motors during the established service life with minimum costs.

Improving the reliability and cost-effectiveness of the operation of asynchronous motors is a complex and many-sided problem requiring a comprehensive solution.

All factors of operational reliability are related and determine the indices of utilization of electric motors and the costs of restoration:

– increasing the service life time and the reliability of motors leads to reducing the number of overhauls and costs of eliminating them;

– ensuring the necessary probability of trouble-free operation allows obtaining high-quality products;

– improving the maintainability of electric motors reduces the service life and costs for planned repairs, maintenance and elimination of the failure consequences;

– increasing the maintenance of electric motors can reduce operating costs.

During operation, the asynchronous electric motor is influenced by various factors. The following types of effects are allocated [1]:

– structural influences caused by initial design defects of the electric motor arising during the manufacture and repair;

– functional ones related to the processes occurring in a working electric motor or working machine;

– environmental impacts (including an operating person who controls the electric motor and performs maintenance and repairs).

An operational state is the state of an asynchronous electric motor, in which it can drive a working machine or a separate node of it (that is, performs its functions according to the purpose) and indicators characterizing its work in nominal mode are within the limits provided by the technical documentation. These indicators are voltage, useful power, power factor, slip, critical moment, efficiency, starting torque, starting current, vibration and noise level, stator winding temperature and others, reflected in the standards and specifications for asynchronous motors.

Monitoring such a number of indicators during the design, production and major repair of electric motors should be provided due to the fact, that the manufacturer or repair company must ensure certain quality including the guarantee of a fail-safe operation of the asynchronous motor in nominal mode for tens of thousands of hours under the operation conditions [2]. During the operation, it is inefficient to monitor such a large number of performance indicators of the electric motor. Therefore, modern diagnostic systems of asynchronous motors determine only a few most significant indicators (depending on the peculiarities of the electric drive functioning) and control them.

Due to the large number of various factors influencing the quality of the asynchronous motor, traditional statistical models, being the basis of diagnostic systems, are not always effective. In this regard, the research and development of intelligent diagnostic systems of electric motors will improve on the process of diagnosing electromechanical systems raising it to a new qualitative level.

2. Analysis of scientific publications. Statement of the problem

The support vector machine (SVM) [3] is a machine algorithm used to classify objects which learns from examples. For example, SVM can distinguish emergency modes of the operation of an electromechanical system and classify them basing on the availability of previous studies of possible technological requirements of operating modes. This approach reveals significant opportunities for constructing adaptive automatic control systems.

The method of support vector machine (SVM) was developed in 1995 by the American corporation AT&T Bell Laboratories. From the very beginning SVM was positioned as an algorithm for solving a classification problem, however, since the end of the 90s of the 20th century, it has also been used to perform regression analysis.

The basis of SVM is a certain mathematical concept, namely, the algorithm of maximizing some mathematical function with respect to the existing set of data. There are four key concepts involved in SVM [4]: the separating hyperplane, the maximum-margin hyperplane, the soft margin, the kernel function.

The separating hyperplane is a mathematical entity that separates classes of objects with the same signs. For example, in Fig. 1, a plane separates balls of light color from dark balls in a three-dimensional space.

The location of the separating hyperplane determined by the SVM method is not unique. There are always many different options for positioning the hyperplane. SVM allows us to choose the optimal placement of the hyperplane. The hyperplane should be located at the maximum distance from the elements of each of the classes, that is, in the middle of a certain zone separating these elements (in Fig. 2, the boundary elements are hatched). This is the essence of the second key concept – the maximum-margin hyperplane.

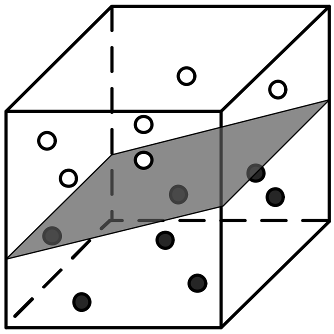

Fig. 1. Example of a separating plane.

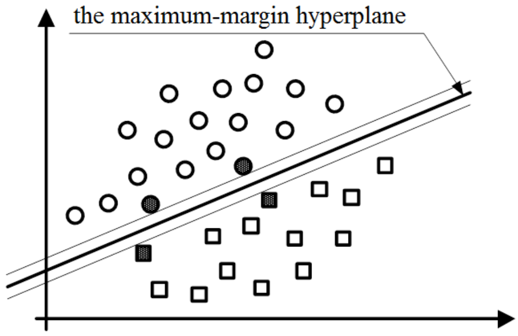

Fig. 2. Location the maximum-margin hyperplane.

Let us conduct a critical analysis of the capabilities of mathematical tools provided by SVM. Classified objects cannot always be separated by a hyperplane. In real systems, errors in the data will occur and, as a result, the hyperplane will not execute the task precisely. Therefore, for the SVM method, the permissible classification error called a soft margin is entered.

Of course, the SVM method should not take into account the excessive errors in the classifications of objects, therefore, an additional parameter should be set which determines how many incorrectly classified objects can cross the maximum-margin hyperplane and how far from it they can be located. Thus, the so-called soft margin of error around the hyperplane is introduced.

Classified objects can be divided linearly only in individual cases. Mostly, they do not allow linear distribution. To solve the linear distribution problem, kernel functions are used that project data from a low-dimensional space into a multidimensional one. With properly selected kernel functions, objects can be separated linearly by a hyperplane in a multidimensional space. Thus, the functions of the kernel act as a directional space.

When the regression problem is solved, the abbreviation of the support vectors method is changed from SVM to SVR (support vector regression) [5]. The advantage of SVR over other methods of regression analysis is that it can determine the parameters of a regression model by solving a quadratic problem with only one solution.

When the support vector method is used, nonlinear regression in the initial space F can be considered as a problem of constructing a linear regression in a certain expanded space H, which has a greater number of measurements than F. This transformation is performed by a nonlinear mapping $\varphi : F \rightarrow H$. Unlike the SVM formulation, where the hyperplane should separate one group of characters from another, the SVR hyperplane is constructed so that as many points as possible fall into it as support vectors or, at least, in a certain zone of confidence regression. The x points lying on this plane can be determined by the formula (1) [6].

$$\vec{w} \cdot \mathbf{X} + b = 0 , \qquad (1)$$

where $\vec{w}$ is the vector normal to hyperplane; $\mathbf{X}$ is the set of vectors $(\vec{x}_1, \vec{x}_2, \ldots \vec{x}_n)$ belonging to the hypersurface $\mathbf{R}^d$; b is a shear factor.

Output information for performing a regression analysis by using the method of support vectors is a learning sample $\mathbf{S} = ((\vec{x}_1, y_1), (\vec{x}_2, y_2), \ldots, (\vec{x}_n, y_n))$. Then the task of linear SVR regression is to find the function

$$f(\mathbf{X}) = \vec{w} \cdot \mathbf{X} + b.$$

With nonlinear regression, using a nonlinear mapping, this function can be represented as

$$f(\mathbf{x}) = \vec{w} \cdot \varphi(\mathbf{X}) + b,$$

where φ is a nonlinear spatial mapping function.

The SVR-analysis reduces the task of finding an optimal hyperplane to the quadratic task of minimizing the functional

$$\min_{w, b, \xi, \xi^*} \left(\frac{1}{2} \|\vec{w}\|^2 + C \sum_{i=1}^{\ell} (\xi_i + \xi_i^*) \right)$$

with the following restrictions:

$$y_i - (\vec{w} \cdot \varphi(\vec{x}_i) + b) \leq \varepsilon + \xi_i ,$$

$$(\vec{w} \cdot \varphi(\vec{x}_i) + b) - y_i \leq \varepsilon + \xi_i^* ,$$

$$\xi_i , \xi_i^* \geq 0, \ i = 1, 2, \ldots, \ell,$$

where C is a positive constant, the greater its value, the greater will be a fine error; ξ_i are variables defining the upper limit of learning error; ξ_i^* are variables that define the lower limit of learning error; ε is the loss function; ℓ is the number of variables that determine the quality of training; $\|\vec{w}\|$ is the Euclidean norm, or vector length.

The loss function is most often piecewise linear (Fig. 3).

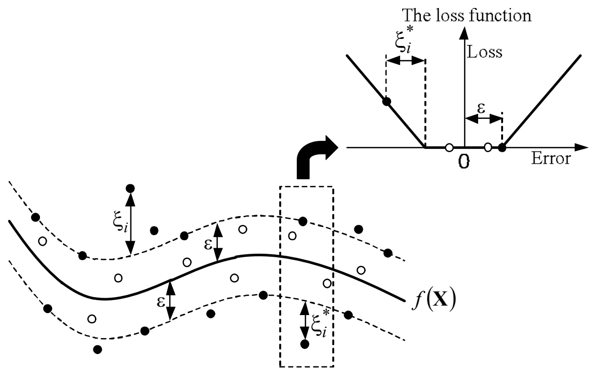

Fig. 3. Implementation of the nonlinear regression analysis by the SVR method.

Sample vectors are the part of the regression task only through their scalar products, so it is possible to use the reflection in the space of signs and pass to the kernel SVM version [7].

In practice, the so-called dual task is most often solved, and the regression function is presented in the following form:

$$f(\mathbf{X}) = \sum_{i=1}^{\ell} (\alpha_i - \alpha_i^*) K(\mathbf{X}, \mathrm{x}_i) + b,$$

where α_i i α_i^* are dual variables satisfying the condition $0 \leq (\alpha_i, \alpha_i^*) \leq C$; $K(\mathbf{X}, \vec{x}_i)$ is a kernel function.

The differences $\alpha_i - \alpha_i^*$ represent weight coefficients ν_i that characterize the contribution of the corresponding support vectors to the formation of the regression function.

The most common kernel functions are the following: the Gaussian radial basis function, linear, polynomial, sigmoidal and exponential radial basis functions.

Regarding the practical meaning of applying SVR analysis to establishing the relationships between the coordinates of the electromechanical system, it can be recommended to apply the linear nuclear function in the case when there is an obvious linear relationship between the values. In all other cases, the qualitative results of the analysis are provided by the Gaussian radial basis function (RBF)

$$K(\mathbf{X}, \vec{x}_i) = \exp\left(-\frac{\|\mathbf{X} - \vec{x}_i\|^2}{2\sigma^2}\right), \qquad (2)$$

where σ is a parameter determining the width of the scope of the loss function.

The advantage of regression analysis with the use of the support vector method is the ability to set the value of ε immediately with forming an appropriate trust zone, in which the error of the correlation between the coordinates can be assumed valid.

The analytical structure of the regression algorithm based on the support vector machine is presented in Fig. 4 [6]. It illustrates the main stages of data processing: setting the values of the test vector, nonlinear mapping, calculating a scalar product or kernel function, summing up the results taking into account weight coefficients and parameter *b*.

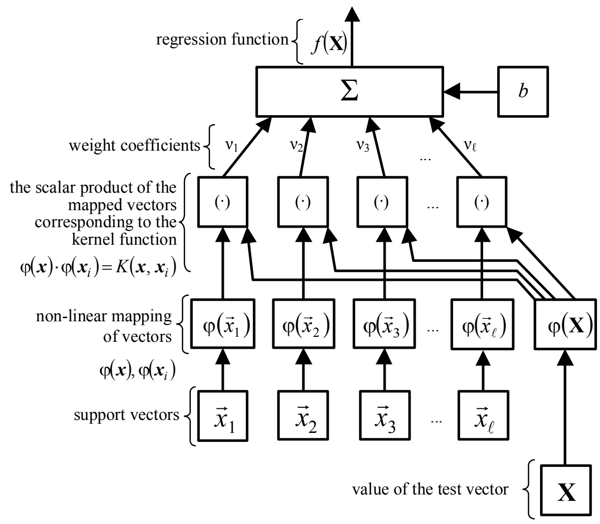

Fig. 4. Analytical structure of regression algorithm based on SVM.

For software implementation of SVR-analysis, in most cases the programming languages C++ or Python are used. SVMlight [8], which has interfaces for Perl, Python, Ruby, Java, .NET, and other programming languages, is the most commonly used software for implementing both classifying and regression tasks using the support vector method. There are also add-ons to the MATLAB software package that extend its functionality by adding SVM support. Among such additions are LIBSVM [9], PRTools [10] and MATLAB SVM Toolbox [11].

The diagnostic system for the asynchronous motor should determine which sets of parameters are acceptable in certain operational situation, and which ones are not. To do this, before training the diagnostic system, a training sample is drawn up that covers all possible variations.

The training sample for the support vector method is formed in such a way that each of the sets of functional parameters corresponds to the state of "able to work" or "disabled". If at least one of the parameters goes beyond the permissible values, then the whole set of parameters will be considered as "disable". In other cases, if all parameters are within the limits of the valid values, the set of parameters will correspond to the state "able to work".

The support vector machine (in the corresponding representation) is used not only for solving the tasks of classification or diagnosis, but also for performing the regression analysis. The basis of verification is a test sample in which the match between the set of parameters and states is introduced.

In order to check the quality of the algorithm a numerical metric is required. Such a metric is often an accuracy. In the simplest case, the metric accuracy (acc)

$$acc = \frac{M}{N} \qquad (3)$$

illustrates what portion of the data was categorized correctly.

3. Objective of the research

The object of the study is the functional state of the asynchronous motor and the electromechanical parameters that characterize its efficiency.

The subject of the study is a regression model designed to diagnose the breakdown of the rods of the short-circuited rotor of the asynchronous motor based on the method of reference vectors.

The objective of the research is to expand the functional capabilities of embedded systems for intelligent diagnostics of electric machines by studying and analyzing a regression model to determine the possible number of broken rods of the short-circuited rotor of the asynchronous motor.

4. Materials and methods of the research

The continuity of technological processes at industrial objects requires reliable operation of all used working mechanisms. For the correct functioning of most operating mechanisms, three-phase asynchronous motors with a short-circuit rotor are used, since such motors are much simpler and cheaper than wound-rotor motors, since the absence of sliding contact rings and starting rheostats reduces the overall dimensions of the machine increasing its reliability.

Often damage to electric motors occurs due to unacceptable long-term work without repair, due to poor storage and maintenance, as well as to the violation of the operating mode for which they are calculated.

The failure rate depends on the duration of the motor operation. The initial period of operation is characterized by the occurrence of motor damage associated with hidden production defects. Typically, after a normal operation period of 15–20 years, there is a gradual increase in failures. This fact is explained by wear and aging of insulating materials and structural elements.

The problem of timely detection of the breakage of the rods of the short-circuited rotor is topical, since the breakdown of the rods in the initial stage is slightly affected by the performance of the electric motor and cannot be detected immediately. Moreover, the breakage of even one rod causes damage to other rods, and, in the long run, it can completely damage the engine, because when the rod is broken, it bends towards the air gap and damages the stator winding. In most cases, it causes rotor eccentricity, which damages the bearings.

Virtually any damage to the electric motor results in the appearance of magnetic and electrical asymmetry. The breakage of the rotor winding rod increases vibrations, decreases the rotational speed under load and causes stator current pulsations consistently in all phases. Violation of contacts, soldered or welded joints is equivalent to the manifestation of the breakdown of turns, rotors or winding wires, depending on the location of the connection.

The breakdown of the stator windings causes asymmetry of currents and the rapid heating of one of the phases. Excessive wear of rolling bearings leads to a disruption of the coaxiality of the motor shaft and mechanism and, as a consequence, to the appearance of the rotor eccentricity. The vibration of the motor increases, and large forces of one-sided gravity occure. Interturn short circuits are asymmetric damages that lead to distortion of the diagram of currents and voltages of the normal mode and are accompanied by a decrease in the motor torque.

In a non-symmetric mode, the stator currents of an electric motor can be expanded to the symmetric components of a direct sequence (DS) and a reverse sequence (RS). Thus, the symmetric components of the stator current can be used to detect many types of defects.

To minimize the influence of structural asymmetry and asymmetry of the supply voltage as a diagnostic parameter, it is more convenient to use the relative value of the RS current in the stator current, i.e., the coefficient of the RS current which is calculated by the following expression [1]:

$$k_{2i} = \left(I_2/I_1\right) \cdot 100\,\%, \tag{4}$$

The magnitude of the RS current also depends on the magnitude of the asymmetry of the supply voltage and the asymmetry of the phase resistances. The connection between asymmetry of currents and voltages is unambiguous. It depends on the parameters of the power network and the motor, as well as on the nature of the asymmetry of their phase resistances.

The frequency f_2 of RS current caused by the breakdown of the rods is a function of sliding s and is determined by expression (5).

$$f_2 = f_1(1-2s) \tag{5}$$

An important parameter used to diagnose the rods of the short-circuited rotor of the asynchronous motor is the pulsation coefficient of the generalized stator current vector γ_i [12, 13].

Thus, for the purpose of intelligent diagnostics of the asynchronous motor, such diagnostic parameters as the RS current coefficient k_{2i} and the pulsation coefficient of the generalized stator current vector γ_i are used. As a training sample, experimental data for the asynchronous motor 4A132M6У3 are used. They are shown in Table 1.

Table 1

Training sample

Number of torn rods, pcs.	P, p.u.	k_{2i}, %	γ_i, %
0	0	0	–
1	0	0.31	0.22
	0.5	0.92	0.65
	1.0	1.60	1.13
2	0	0.63	0.45
	0.5	1.89	1.34
	1.0	3.23	2.28
3	0	0.86	0.61
	0.5	2.3	1.63
	1.0	4.1	2.90

For the data presented in Table 1 the support vector machine method in its regression representation is applied. This retains all the main functions characterizing the algorithm (hyperplane of the maximum limit, support vectors, etc.). The support vector regression (SVR) uses the same principles as SVM for classification with only a few minor differences. Like SVM, SVR can use different kernel functions to increase the accuracy of regression analysis (Fig. 5).

The direct implementation of intelligent diagnostics is carried out by Scikit-Learn, a machine learning library for the Python programming language. The Scikit-Learn library allows implementing the support vector machine for solving classification and regression problems. The SVC, NuSVC, and LinearSVC classes are available for classification using the support vector method. They also can e used for performingtheregression analysis [14].

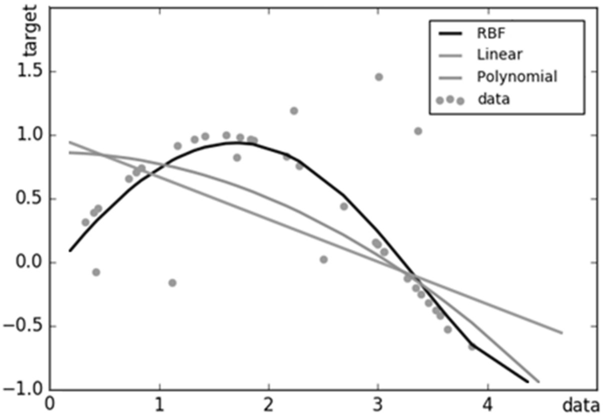

Fig. 5. Example of a regression analysis with three different kernel functions (RBF, Linear, Polynomial).

The classic regression analysis conducted by support vector machine is implemented with the use of the SVR class from the Scikit-Learn library, which, unlike the LinearSVC, allows using five types of kernel functions. Some SVR class options available to the user are:

– *C* – the penalty parameter (by default is equal to one);

– *epsilon* – the value in the SVR model, indicating the limit in which the loss function is not associated with penalty;

– *kernel* – defines the type of kernel function that will be used in the algorithm; should be one of the following: *linear*, *poly*, *rbf*, *sigmoid*, *precomputed (rbf* by default);

– *degree* – the degree for the polynomial kernel (it is 3 by default);

– *gamma* – the kernel coefficient (for the kernel functions *rbf*, *poly* and *sigmoid*); if the gamma parameter is set to *auto*, then *1/n_features* will be used instead, where *n_features* is the number of instances of the training sample);

– *shrinking* – indicates the use of diminutive heuristics (it is *True* by default);

– *tol* – tolerance to the termination of the model learning (it is 10^{-3} by default).

5. Software implementation of the proposed solutions

Software SVR analysis of the experimental data was performed by constructing nine separate models:

– model with linear kernel at $P = 0$;

– model with RBF-kernel at $P = 0$;

– model with polynomial kernerl (*degree* = 5) at $P = 0$;

– model with linear kernel at $P = 0{,}5$;

– model with RBF-kernel at $P = 0.5$;

– model with polynomial kernel (*degree* = 5) at $P = 0.5$;

– model with linear kernel at $P = 1$;

– model with RBF-kernel at $P = 1$;

– model with polynomial kernel (*degree* = 5) at $P = 1$.

The models are grouped into three separate Jupyter Notebook files [15] by the load factor, that is, in the first file all models with $P = 0$ are put, in the second one all models with $P = 0{,}5$ are written, in the third one all models with $P = 1$ are located.

Fig. 6 shows the program code of the block designed to perform SVR analysis of experimental data at $P = 0$. The result of the work of this block is shown in Fig. 7.

```
%matplotlib inline

import numpy as np
from sklearn.svm import SVR
import matplotlib.pyplot as plt

###################################################
# Give sample data Load = 0                       #
###################################################
X = np.array([[0],
              [0.31],
              [0.63],
              [0.86]])
y = np.array([0, 1, 2, 3])
print(X, y)

###################################################
# Fit regression model                            #
###################################################
svr_rbf = SVR(kernel='rbf', C=1e3, gamma=0.01)
svr_lin = SVR(kernel='linear', C=1e3)
svr_poly = SVR(kernel='poly', C=1e3, degree=5)
y_rbf = svr_rbf.fit(X, y).predict(X)
y_lin = svr_lin.fit(X, y).predict(X)
y_poly = svr_poly.fit(X, y).predict(X)
###################################################
# Look at the results                             #
###################################################
lw = 2
plt.figure(figsize=(6,4))
plt.scatter(X, y, color='darkorange', label='data')
plt.plot(X, y_rbf, color='navy', lw=lw,
         label='RBF model')
plt.plot(X, y_lin, color='c', lw=lw,
         label='Linear model')
plt.plot(X, y_poly, color='cornflowerblue', lw=lw,
         label='Polynomial model')
plt.xlabel('data')
plt.ylabel('target')
plt.title('Support Vector Regression')
plt.legend()
plt.show()
```

Fig. 6. Program code for executing the SVR-analysis of experimental data at P = 0.

A similar program code is created for $P = 0.5$ and $P = 1$, based on the data presented in Table 1. The results of this program code are shown in Fig. 8 and Fig. 9.

The series of similar experiments having been repeatedly conducted, it was found that the error depends on both the accuracy of the experimental data and the width of the scope of the kernel function (the penalty parameter of the SVR class).

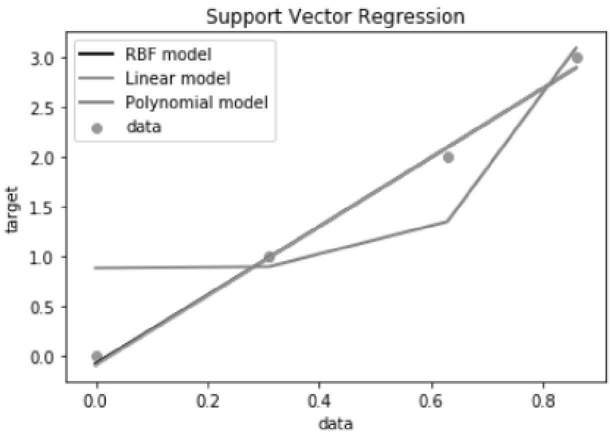

Fig. 7. Result of executing the program code designed to perform the SVR-analysis of experimental data at P = 0.

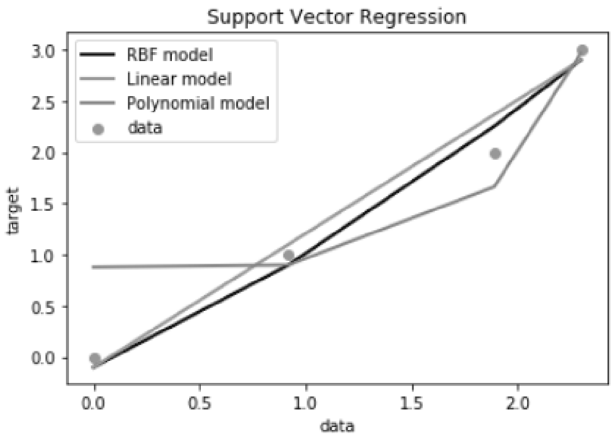

Fig. 8. Result of executing the program code designed to perform the SVR-analysis of experimental data at P = 0.5.

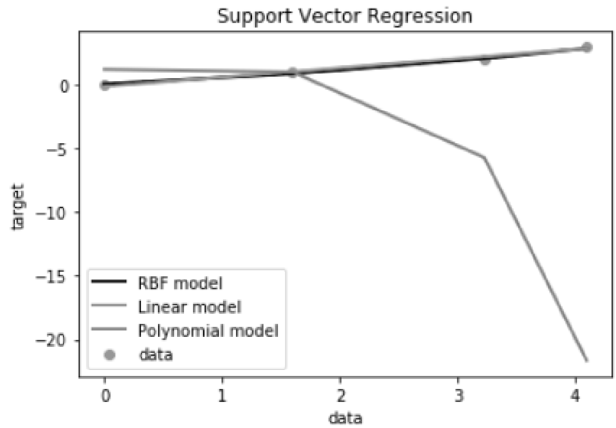

Fig. 9. Result of executing the program code designed to perform the SVR-analysis of experimental data at P = 1.

6. Results of the research

The results of the SVR-analysis of the experimental data (including the actual values of the broken rods and those provided for the value model) are summarized in Table 2. The metric *acc* was determined by formula (3); according to the above experiments, its value exceeds 0,9. This table also reveals that the smallest mean-square deviation occurs while using the SVR model with RBF-kernel. The model with polynomial kernel turns out an inadequate.

Hence, increasing the accuracy of experimental data and reducing the zone of insensitivity of the loss function *epsilon* contributes to reducing the error of regression analysis after the appropriate retraining of the SVR algorithm.

Table 2

Results of the SVR-analysis of experimental data

P, p.u.	Actual number of broken rods	The number of torn rods provided by linear model	Absolute value of the error of linear model	The number of torn rods provided by RBF model	Absolute value of the error of RBF-model	The number of torn rods provided by polynomial model (*degree*=5)	Absolute value of the error of polynomial model
0	0	–0.0913	0.0913	–0,0772	0,0772	0,8865	0,8865
	1	0.9869	0.0131	0,9896	0,0104	0,9	0,1
	2	2.0999	0.0999	2,1	0,1	1,3534	0,6466
	3	2.9	0.1	2,8999	0,1001	3,1	0,1
0,5	0	–0.1	0.1	–0,0997	0,0997	0,8775	0,8775
	1	1.1	0.1	0,8993	0,1007	0,899	0,101
	2	2.3653	0.3653	2,2525	0,2525	1,6614	0,3386
	3	2.9001	0.0999	2,9002	0,0998	2,9696	0,0304
1	0	–0.1	0.1	0,1003	0,1003	1,2545	1,2545
	1	1.0709	0.0709	0,8994	0,1006	1,047	0,047
	2	2.2637	0.2637	2,1061	0,1061	–5,7033	7,7033
	3	2.9004	0.0996	2,9003	0,0997	–21,6745	24,6745
Mean-square deviation		0,1522		0.1159		7.4825	

The advantage of the SVR-analysis is the unambiguous convergence of the regression algorithm; reducing the penalty parameters should be performed with an increase in the accuracy of the experiments.

7. Discussions

Correlation relations between controlled coordinates are used in the presence of statistical relationships between them, which are illustrated by the correlation field or correlation coefficient. The regression analysis, in contrast to the correlation, does not determine how significant the relationship between values is, but it searches for a model of this connection in the form of some regression function. The regression relationship between controlled coordinates is convenient to use when the relationship between them is quantitatively expressed as numerical combinations. It can be both experimentally obtained data and some calculation points that characterize the relationship between controlled coordinates. The application of the support vector method to performing a regression analysis gives a number of advantages over traditional approaches.

SVM allows solving complex nonlinear regression problems with a limited volume of the training sample. Essential requirements for computer technology are advanced only at the stage of model training. At the same stage of its operation, it is enough to apply a single-board microcomputer, on which the developed software code in Python can be run. In the course of experimental studies, a trained model showed successful functioning on a single-board computer Raspberry Pi 2.

The duration of the model training by SVM is mainly determined by the time of solving the corresponding quadratic programming problem. Therefore, the theoretical and empirical complexity depends on the method of solving this problem. It is believed the duration of the solution of the quadratic programming problem to be proportional to the cube of the available data.

8. Conclusion

The regression model based on the support vector method is used to determine the number of damaged rods of the short-circuited rotor of the asynchronous motor. The efficiency of the model is confirmed by experimental studies. It is found that the SVR model with the RBF-kernel has the smallest value of the mean-square deviation.

On the basis of the performed research, it can be concluded that in cases where it is necessary to use a regression relationship between controlled coordinates, the SVR-analysis has significant prospects; it has the following advantages over other methods:

– parameters of the regression model are determined by solving a quadratic programming problem having only one solution;

– it is possible to set up a trust zone around the main regression line, in which the correlation error between coordinates is considered permissible;

– reference target function formed as a result of the SVR-analysis can be easily modified by re-training the SVR algorithm and does not require the selection of special regression dependencies, since all necessary functionalities have already been incorporated into the kernel function.

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РЕГРЕСІЙНИЙ АНАЛІЗ ПРАЦЕЗДАТНОСТІ АСИНХРОННИХ ЕЛЕКТРОДВИГУНІВ НА ОСНОВІ МЕТОДУ ОПОРНО-ВЕКТОРНОЇ КЛАСИФІКАЦІЙНОЇ МАШИНИ

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Актуальність теми статті полягає в тому, що запропонована методика здійснення регресійного аналізу працездатності асинхронних двигунів є невибагливою до точності вимірювання величин, за якими здійснюється регресійний аналіз, та до об'єму навчальної вибірки, тому вона може знайти застосування у сучасних вбудовуваних системах діагностування.

Мета роботи – розширити функціональні можливості вбудовуваних систем інтелектуального діагностування електричних машин шляхом навчання та аналізу регресійної моделі для визначення можливої кількості обірваних стрижнів короткозамкненого ротора асинхронного двигуна.

Методи дослідження засновані на використанні опорно-векторної класифікаційної машини, що застосовується у регресійному представленні. За такого підходу параметри регресійної моделі визначаються за допомогою розв'язання задачі квадратичного програмування, що має лише один розв'язок. Для визначення значень параметрів, що використовуються для навчання моделі, застосовують загальну теорію перехідних процесів у машинах змінного струму, методи математичного моделювання, обчислювальної математики, методи визначення симетричних складових узагальнених векторів.

Розроблено методику здійснення регресійного аналізу працездатності асинхронних двигунів на основі методу опорно-векторної класифікаційної машини, що дозволяє визначати як наявні несправності та пошкодження електричної машини, так і передбачити їхнє можливе виникнення у найближчому майбутньому.

Розроблена на базі методу опорних векторів регресійна модель дозволяє визначати кількість пошкоджених стрижнів короткозамкненого ротора асинхронного двигуна. Ефективність моделі підтверджено у результаті експериментальних досліджень. Встановлено, що найменше значення середньоквадратичного відхилення має регресійна модель з радіально-базисною функцією ядра. Отже, в тих випадках, коли необхідно використовувати регресійний зв'язок між керованими координатами, значні перспективи має застосування методів машинного навчання, заснованих на моделі векторного простору, мета яких – знайти поділяючі поверхні між класами, максимально віддалені від усіх точок навчальної множини.

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