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IDENTIFICATION OF INDUCTION MACHINE PARAMETERS USING SUPPORT VECTOR MACHINES

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Abstract: The paper presents the application of the support vector machines (SVM) to identify the parameters of the induction machine. The task is related to the regression problem, solved using a separate SVM for each parameter of the analysed object. The purpose and significance of the research is explained. Then, rules of usage and advantages of SVM are introduced. The proposed approach is realised using the model of the induction motor. Importance of the correct SVM kernel and its parameters selection are explained in detail. The paper is concluded with results discussion, conclusions and future prospects.

Keywords: electrical machines, artificial intelligence, regression, fault identification

1. INTRODUCTION

The analysis and modeling of electrical machines is an important part of the industrial applications of computational methods. It requires the advanced mathematical apparatus and computer software to simulate models and identify their actual state. Knowledge about relations between the internal state of the machine and its responses observed on the accessible and partially accessible outputs (nodes) are used by designers to eliminate construction flaws. On the other hand, users of such equipment know, which part of the machine must be repaired or replaced to maintain the correct work regime.

The induction (asynchronous) motors are popular drives widely used in the industry. They are cheaper and simpler than DC or wound rotor motors [1]. To ensure the desired behavior of such a motor, methods for its constant on-line monitoring must be developed. The mathematical analysis of the electrical machinery requires considering multiple physical phenomena (related to the effects in the actual working environment). Therefore computer-based models [2] are often used here. They are crucial in obtaining knowledge about the behavior of the device in extreme situations and design methods for the accurate identification of the motor's state. Additional problems are tolerances of parameters and additive noise. They must be considered during the analysis of the model and real system.

The paper presents the support vector machines (SVM) regression approach to identify the values of the induction machine parameters. This technique can be used to correctly diagnose the machine's state as the part of the fault detection, location and identification scheme. The proposed approach is more accurate than the more popular methods exploiting the state classification algorithms. In section 2 the parameter identification task is defined. Section 3 contains description of the SVM application for the presented task. In section 4 description of the analyzed asynchronous machine is provided. Experiments with the proposed scheme are in section 5, while results discussion and conclusions are in section 6.

2. PARAMETER IDENTIFICATION TASK

The task of identifying parameters of the machine is based on its responses recorded at the accessible or partially accessible nodes. The work regime of the analyzed system is represented by the function (1)

$$\boldsymbol{y}=f(\boldsymbol{p},\boldsymbol{x},\boldsymbol{t}) \quad (1)$$

where $\boldsymbol{p}$ is the vector of its n internal parameters, $\boldsymbol{x}$ is the set of excitation signals imposing the response of the system, $\boldsymbol{y}$ is the set of l observable responses generated by the machine and $\boldsymbol{t}$ is the discrete time. The system's diagnostics consists in performing the reverse operation, i.e. finding information about $\boldsymbol{p}$ based on $\boldsymbol{y}$ (after delivering to the input $\boldsymbol{x}$), as the decomposition of the system into its constituent parts is neither possible, nor practical. Obtaining $\boldsymbol{y}$ is possible through the online measurements of output signals. They contain the information about the internal state of the system. Such a task is difficult, as the relation between parameters and responses driven by their values is complex (the function f is not easily reversible). There are four problems in machine diagnostics. Firstly, there are ambiguity groups of parameters resulting in the identical responses of the system. Secondly, parameters' values are affected by the tolerance margins. Real elements of the machine are manufactured with finite precision and their values change with time. These effects make the fault detection difficult. Thirdly, machines work in the presence of noise. Finally, the number of experts with the deep knowledge about behavior of such systems is limited. Therefore, for the diagnostic task heuristic approaches are employed [3].

The information about the system's state includes three aspects: detection, location and identification. The first one consists in determining the change in the state of the system from the nominal (desired) one. The second is gaining knowledge about the source of changes (finding the parameter responsible for the deviation). The third is determining the real value of the faulty parameter. All three aspects can be considered as the classification task. Identifying the parameters' values is the regression task (2), being the scope of this paper. Here, the method must be employed to map the l-sized vector of the measured values into the single parameter's real value.

$$R^l \rightarrow R \tag{2}$$

The approach requires the input vector containing the information from the machine responses. It produces the output – the actual value of the analyzed parameter.

The main problem here is the extraction of the characteristic features from output responses. The process depends on the particular system and requires obtaining the knowledge about its behavior. The feature (stamp or symptom) can be, for instance, the maximum value of the torque in the stable state or the stator current in the predefined time instant.

The analysis of electric machinery requires identification of multiple parameters at the same time. This expands the scheme (1) into multiple values to calculate, based on features form the measured responses. Therefore the methodology must be multiplied and applied for each parameter separately.

3. APPLICATION OF SVM TO THE PARAMETER IDENTIFICATION

The SVM are the popular method for the analysis of data originating from various domains. The SVM regression requires finding the function mapping measured values from (1) into the system's parameter values (2).

$$\boldsymbol{p}=f(\boldsymbol{y})=\boldsymbol{w}^T\boldsymbol{y}+b \tag{3}$$

where $\boldsymbol{w}$ is the set of weights of SVM and b is the free real-valued element. For the applied excitations $\boldsymbol{x}$ and observed responses $\boldsymbol{y}$ the SVM attempt to reverse the function (1). The goal is to find $f(\boldsymbol{y})$ fitting best the presented data and having the simplest form. The typical optimization of SVM is in (4), where ε is the acceptable error between the actual o and obtained $f(\boldsymbol{x})$ values.

$$\begin{aligned}&minQ(\boldsymbol{w},b)=1/2\cdot\boldsymbol{w}^T\cdot\boldsymbol{w}\\&\text{with constraints: } |o_i-\boldsymbol{w}^T\cdot\boldsymbol{y}_i-b|\leq\varepsilon\end{aligned} \tag{4}$$

where $i=1,\ldots,k$ is the number examples presented to SVM. They are sets of symptoms obtained after a single simulation of the induction machine model (5). This problem is transformed into the dual form, which makes it usable for non-linear cases [4]. The most popular method of SVM training is the quadratic programming [5].

Because SVM consider erroneous or inaccurate data, they are better suited for the analysis of noisy and complex systems, including existence of ambiguity groups. The core part is the transformation of the data set from the original space into the new one, using the kernel function. The aim is to increase the regression accuracy. Although multiple functions can be used here [5], the most popular are, linear, polynomial, sigmoidal, Fourier and radial basis functions (RBF). Every function (except linear) requires setting its parameters. For the most popular RBF kernel it is the width of the function (the value of the standard deviation). Determining the optimal kernel type and its parameters depends on the particular problem and is one of the main tasks for the designer [6].

The SVM training requires providing learning and testing data sets, containing k examples of the motor's behavior (5). The sets are constructed using the data from the motor model simulation, each time performed after introducing the change to one of n parameter's values. The particular parameter is represented by the equal number of rows in the set to provide uniform amount of data regarding every fault. The nominal state (where all parameters have the values provided by the designer) is also considered. The set is the table A (4), in which every of k rows is the result of the single motor simulation. It contains l values of features a_{ij} (where $i=(1,\ldots,k)$ and $j=(1,\ldots,l)$), extracted from the responses. They are supplemented with the information about the actual value of the parameter being the source of the problem. It is represented by two additional columns containing, the identifier of the parameter p_a (where $a=(1,\ldots,n)$) and one of its m values selected for experiments (v_{ab}, where $b=(1,\ldots,m)$). Remaining parameters in each example are assumed nominal. This makes the set suitable for classification and regression tasks. The accuracy of the approximation depends on the number of examples in the training data set. The number of values for each parameter determines the number of points to approximate by the SVM.

$$A=\begin{bmatrix} a_{11} & a_{12} & & a_{1l} & p_1 & v_{11} \\ a_{21} & a_{22} & & a_{2l} & p_1 & v_{12} \\ & & \cdots & & & \\ a_{k1} & a_{k2} & & a_{kl} & p_n & v_{nm} \end{bmatrix} \tag{5}$$

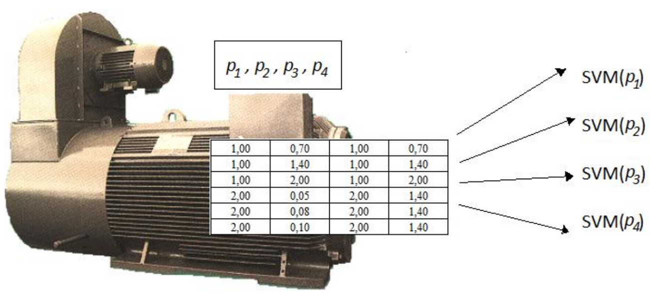

Fig. 1. Scheme of applying multiple SVM modules to approximate parameters of the induction motor

The SVM approach was used here according to the scheme in Fig. 1, where each SVM module is trained to monitor the separate parameter (here four) of the machine. This allows for the simultaneous approximation of all considered parameters, leading to mapping $R^l \rightarrow R^n$. The disadvantage of the method is the considerable computational effort imposed by training each SVM module. It is now *n* times greater than in (2). Therefore the ability to implement this method in the on-line application must be verified. The idea is similar to [7], where multiple SVMs were used for the multiple faults classification. The regression gives more precise answer about the system's state. Unfortunately, it is also more difficult to achieve the acceptable accuracy, especially after introducing parameter tolerances and the influence of noise.

Two approaches are proposed to solve the diagnostic task. In the first one, the whole data set is used to train the SVM module responsible for the particular parameter. In each case the last two columns in the set are changed to represent only the actual value of the considered parameter. In most rows this will be the nominal value of the parameter. The example of the transformation between the original data set and the data set adjusted for the particular SVM is in Fig. 2. Here the SVM is trained to react to the first parameter, which nominal value is 1.4. In the testing stage, all SVM modules are activated at the same time, each producing the expected value of one parameter.

p_a	v_{ab}
1,00	0,70
1,00	1,40
1,00	2,00
2,00	0,05
2,00	0,08
2,00	0,10

p_a	v_{ab}
1,00	0,70
1,00	1,40
1,00	2,00
1,00	1,40
1,00	1,40
1,00	1,40

Fig. 2. Transformation of the descriptive columns of the original data set into the form suitable for the particular SVM

The second approach consists in training each SVM only for the data subset containing the information about the selected parameter. The original set *A* is divided into *n* subsets with examples defining changes in one separate parameter. This approach obtains the high accuracy much easier, but must be combined with another (classification) method for pre-processing the data and making decision about which SVM module to activate. This way only one value of the parameter is produced in the testing stage (remaining are assumed nominal). The efficiency of such an approach depends mainly on the accuracy of the classification method. The computational effort is also smaller, determined by only one running SVM module.

Both methods were tested assuming infinitely accurate values of motor parameters as well as with values affected by the tolerances and additive noise. The tolerances were set at 10 percent for each parameter, which is the value acceptable in practice []. The additive noise was added to the responses after the machine simulation. Before the SVM could be implemented, the responses were de-noised. The analysis of induction machine behavior in the presence of noise is currently performed using the discrete or packet wavelet decomposition []. In the presented work the discrete wavelet transform was used to eliminate high-frequency components []. From cleared responses stamps are extracted. As the de-noising procedure deforms system responses, its influence on the regression accuracy may be similar to the tolerance margins of parameters. Both effects were verified experimentally. The proposed methods were implemented in the MATLAB environment using SVM toolbox [5].

4. INDUCTION MACHINE

Asynchronous motors are alternate current machines. Their work regime consists in rotating the rotor inside the changing magnetic field created by the current flowing through the stator. Modeling of such a device is well established [9]. The typical model is described by the equations (6) [10]:

$$\begin{aligned}
\frac{di_{sd}}{dt} &= \frac{\beta}{T_R}\cdot\varphi_{rd} + \beta\cdot n_p\cdot\omega_r\cdot\varphi_{rq} - \gamma\cdot i_{sd} + \frac{1}{\sigma\cdot L_s}\cdot u_{sd}\\
\frac{di_{sq}}{dt} &= \frac{\beta}{T_R}\cdot\varphi_{rq} - \beta\cdot n_p\cdot\omega_r\cdot\varphi_{rd} - \gamma\cdot i_{sq} + \frac{1}{\sigma\cdot L_s}\cdot u_{sq}\\
\frac{d\varphi_{rd}}{dt} &= -\frac{1}{T_R}\cdot\varphi_{rd} - n_p\cdot\omega_r\cdot\varphi_{rq} + \frac{M}{T_R}\cdot i_{sd}\\
\frac{d\varphi_{rq}}{dt} &= -\frac{1}{T_R}\cdot\varphi_{rq} - n_p\cdot\omega_r\cdot\varphi_{rd} + \frac{M}{T_R}\cdot i_{sq}\\
\frac{d\omega}{dt} &= \frac{M\cdot n_p}{J\cdot L_r}\cdot\left(i_{sq}\cdot\varphi_{rd} - i_{sd}\cdot\varphi_{rq}\right) - \frac{C_e}{J}
\end{aligned}\tag{6}$$

where electrical parameters are: i_{sd}, i_{sq} (*d*- and *q*-axis components of the stator current), φ_{rd}, φ_{rq} (*d*- and *q*-axis components of the rotor flux linkages), T_R (the rotor time constant), n_p (the number of magnetic pole pairs), L_s, L_r, M (stator, rotor and mutual inductances), u_{sd}, u_{sq} (*d*- and *q*-axis components of the stator voltage). The mechanical parameters are: ω_r (the rotor angular speed), σ (the total leakage factor), C_e (torque) and J (inertia). Coefficients β and γ are defined as (7):

$$\begin{aligned}
\beta &= \frac{M}{\sigma\cdot L_s\cdot L_r}\\
\gamma &= \frac{R_s}{\sigma\cdot L_s} + \frac{M^2\cdot R_r}{\sigma\cdot L_s\cdot L_r}
\end{aligned}\tag{7}$$

The model was simulated in the SIMULINK environment.

Seven analyzed parameters of the considered motor and their nominal values were $R_s=2.25\ \Omega$, $L_s=0.1232\ H$, $L_r=0.1122\ H$, $M=0.1118\ H$, $T_r=0.16\ s$, $\sigma=0.09$, $J=0.0504$. The remaining parameters remained unchanged at their nominal values throughout the test: $R_r=0.7\Omega$, $n_p=3$. Each analyzed parameter was assigned seven values, leading to 49 total rows in the training and testing data set.

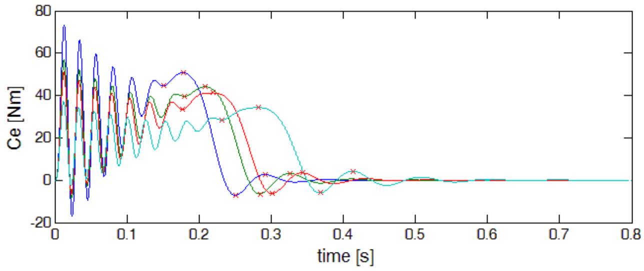

Fig. 3. Induction motor's torque for various values of R_s.

Motor responses were analyzed in the startup phase. Four signals were observed: the stator current vector I_s, torque C_e, angular speed ω, and rotor flux φ_r. From each signal, characteristic features were collected. For instance, from the torque (Fig. 3) time instants and values of four extremes before reaching the stable state were extracted.

5. EXPERIMENTS

Seven SVM modules were designed to determine the value of subsequent parameters. Their usefulness was verified as the standalone method (working for the whole data set) and as the module reacting only to the particular subset of examples. In both cases the comparison between kernels was performed to select the best one for the task. The parameter values for the selected kernels were also optimized using the simulated annealing method from [11]. In both cases, multiple kernels were considered, i.e. RBF, ERBF, polynomial, Fourier or linear.

The experiments were conducted to verify the regression quality when training and testing SVM on the data obtained:

- from the ideal SUT, i.e. without the additive noise and tolerances
- after introducing tolerances to the SUT model
- after clearing responses of the SUT (which was simulated and then additive noise added to the signals)
- from various number of SUT simulations (determining the number of examples in the sets)

5.1. Standalone SVM regression

All modules were trained to react on all examples in the data set. Only radial basis functions were appropriate for the task. The key operation was selection of the kernel parameter. To select its optimal value, the measure was constructed to minimize the difference between the expected value in the nominal state and the faulty states (8):

$$E = \alpha_1 \cdot E_{nom} + \alpha_2 \cdot E_{fault} \tag{8}$$

where E_{fault} is the MSE for m examples with parameter values different from the nominal (9):

$$E_{fault} = \frac{1}{m} \cdot \sum_{i=1}^{m} (\gamma_i - p_i)^2 \tag{9}$$

and E_{nom} is the mean square error (MSE) for k-m examples containing the nominal value of the motor parameter (10):

$$E_{nom} = \frac{1}{k-m} \cdot \sum_{i=1}^{k-m} (\gamma_i - p_i)^2 \tag{10}$$

In (9) and (10) γ is the actual value of the parameter, while p is the value produced by the SVM. Weights $\alpha_1, \alpha_2 \in (0,1)$ and $\alpha_1 = 1 - \alpha_2$ determine, how important is the accurate expression of the parameter values in the nominal state and faulty ones. Usually errors made for the nominal state are greater than errors for the faulty states and require a compromise from the designer. Two values were verified: $\alpha_1 = \alpha_2$ and $\alpha_1 = 0.6$, $\alpha_2 = 0.4$. The latter case gives the greater importance to the correct fault detection than the identification (as approximating the nominal value of the parameter is more important than its deviation). Therefore it was eventually selected for the tests. The procedure was repeated for every selected kernel.

From all available kernels, three were useful, i.e. RBF, ERBF and polynomial. Remaining kernels were giving much worse results to be used in practice. The verified kernel values were the width of the radial basis function (for the first two) and the degree of polynomial (for the third kernel). In the first two cases the acceptable approximation results was obtained for large values of the parameter (such as 1e+6), while in the third one it was below 1 (such as 1e-3). The influence of the RBF parameter on the approximation errors for L_s SVM is in Fig. 4.

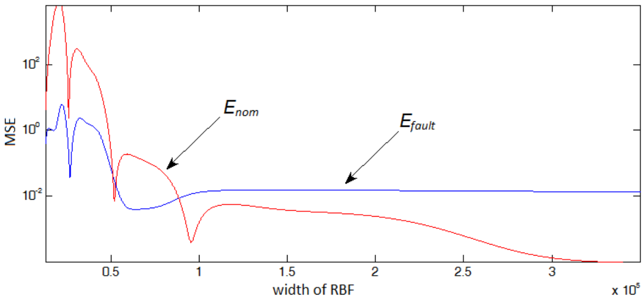

Fig. 4. Influence of the width of the RBF kernel on E (8) for L_s

The main problem was to find the error value minimizing values of E_{fault} and E_{nom}. As they have minimal values for different values of the parameter, the weights α_1, α_2 selection was the decisive step.

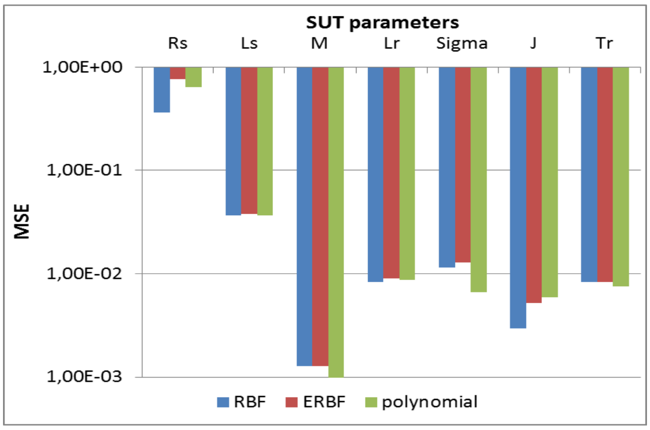

Fig. 5. Error (8) of the ideal SUT's parameters identification for three kernel types (standalone regression)

The optimal values of the combined MSE for the ideal SUT are in Fig. 5. Various SUT parameters are approximated with different accuracy. This depends on the range of the SUT parameter values represented in the data set and the relation between the actual values and the change of the symptoms position in the SUT responses. Parameters R_s and L_s are the most difficult to represent., while all other are identified comparably. The difference between the particular kernels has minor impact on the diagnostic efficiency. The best results are obtained for RBF or polynomial functions, although different values of the kernel parameters had to be used (Table 1)

Table 1: Kernel parameters ensuring the optimal SUT parameter identification (standalone regression)

SUT parameter	Kernels		
	RBF	ERFB	polynomial
R_s	1,73E+06	4,83E+07	1,80E-02
L_s	1,00E+06	1,24E+08	5,59E-03
M	3,63E+11	3,11E+08	6,04E-03
L_r	1,40E+07	5,20E+07	7,53E-03
Sigma	2,02E+09	1,07E+08	7,20E-02
J	1,87E+06	6,22E+07	1,00E-07
T_r	8,24E+08	1,00E+09	9,12E-03

Introduction of tolerances to the SUT parameters decreased diagnostic accuracy only for the mutual inductance *M*. Identification of remaining parameters' values is at the same level. Also, the quality of all kernels remains practically the same. The results show the SVM are resilient to the slight changes in the SUT parameters values (up to 10 percent).

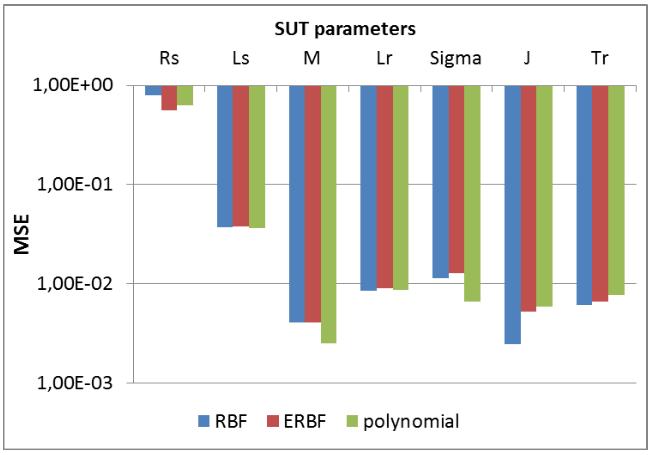

Fig. 6. Error (8) of SUT parameters identification for three kernel types considering parameter tolerances (standalone regression)

Introducing the noise to the induction machine responses requires the denoising procedure. After applying the Daubechies wavelets (between db2 and db8) to clear the waveform (separating the low-frequency part from the noise), the stamps were extracted as before. Results obtained such data sets are similar to the ones with tolerances. The diagnostic efficiency depends here on the denoising operation. If it is executed properly and responses are not deformed (by cutting off too large part of the low frequency components), the efficiency of SVM is similar as when introducing the tolerance of parameter values.

The exemplary output of the SVM for L_s and T_r is in Table 2. As can be seen, the regression accurately predicts the nominal state or faulty ones, but it's difficult to obtain a high accuracy for both. For most examples parameter values are within 10 percent of the actual value.

Table 2. Exemplary approximation results for L_s and T_r

L_s		T_r	
p	o	*p*	o
0,1241	0,123	0.1916	0.1600
0,1254	0,123	0.0835	0.0500
0,1309	0,123	0.0719	0.1000
0,0031	0,063	0.1535	0.1400
0,8439	0,9	0.1806	0.1800
0,1428	0,164	0.2143	0.2400
0,1521	0,21	0.1674	0.1600
0,123	0,123	0.1618	0.1600

5.2. Combined SVM regression

This scheme was applied with much greater success, as multiple kernels performed the parameter identification. After the fault detection is performed, the SVM is used only to locate fault, i.e. determine the parameter value knowing it is outside the nominal boundaries. The experiments were conducted in the same manner as for the standalone regression. This time only (9) mean square error had to be calculated, as the SVM did not have to detect the nominal values of the SUT parameters. In the combined regression more kernels could be used, including linear or spline. These are attractive, because don't have parameters. Therefore during the diagnostic module design the time consuming optimization procedure is omitted. Unfortunately, their usefulness is limited, as other kernels give better results.

Fig. 6 shows that this time RBF kernel is significantly better in most situations. Polynomial and ERBF kernels are comparable, other kernels are usable, but their efficiency is most of the time worse. The error (8) is much smaller than for the standalone regression. This is because the SVM is trained on smaller data set, simpler for the analysis.

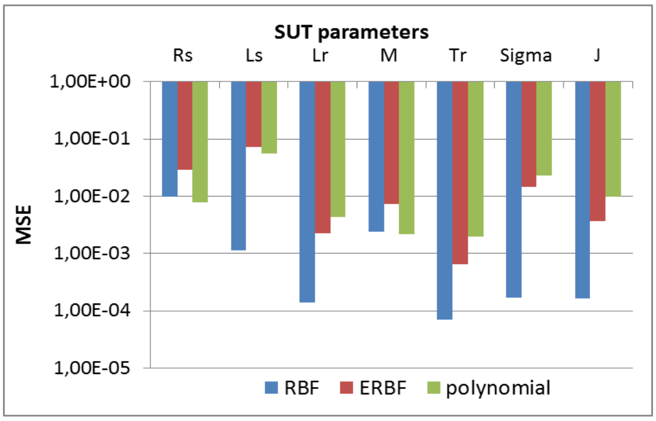

Fig. 7. Error (8) of the ideal SUT's parameters identification for three kernel types (combined regression)

The optimal values of kernel parameters delivering minimal error (8) are in Table 3. They are smaller for RBF and ERBF and larger for polynomial than in the standalone regression. This time it's easier to adjust regression machines to the data.

Introduction of tolerances resulted in similar effect as for the standalone regression. Although the error increased for some SUT parameters, it is still small (Fig. 8). The increase of the identification accuracy was obtained after doubling the number of examples in the data sets. Fig. 9 shows results for SVM trained and tested on 14-example subsets. For larger number of points the regression works much better. Again the RBF kernel is the best.

Table 3: Kernel parameters ensuring the optimal SUT parameter identification (combined regression)

SUT parameter	Kernels		
	RBF	ERBF	polynomial
R_s	1,40E+06	8,92E+03	1,00E-01
L_s	5,20E+06	2,26E+05	4,04E-02
L_r	4,82E+07	1,25E+05	2,28E-02
M	4,80E+06	1,00E+07	1,00E-01
T_r	1,00E+06	9,32E+04	9,75E-02
Sigma	8,60E+06	2,58E+05	1,21E-02
J	1,80E+06	1,91E+05	1,69E-02

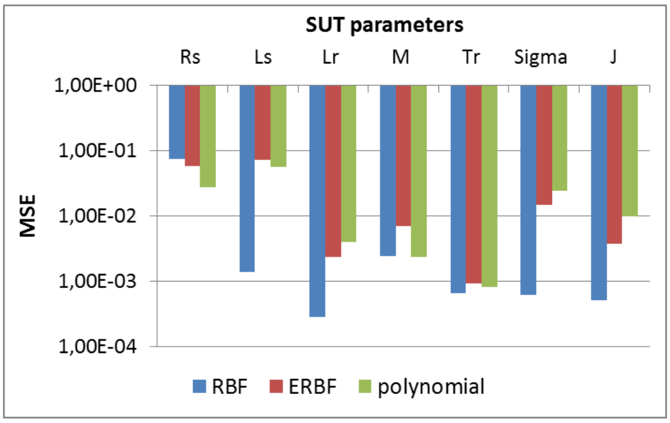

Fig. 8. Error (8) of SUT parameters identification for three kernel types considering parameter tolerances (combined regression)

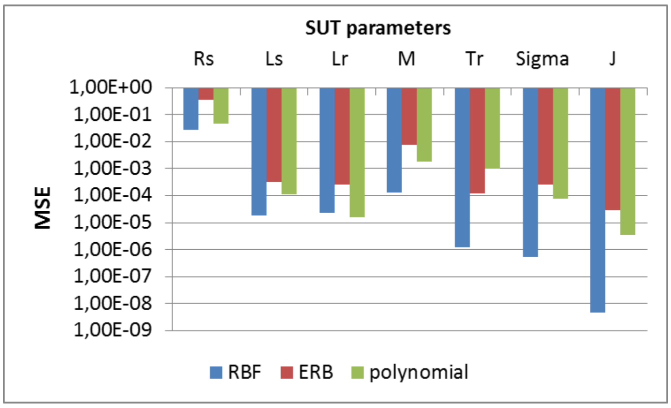

Fig. 9. Error (8) of SUT parameters identification for three kernel types working on larger data set (combined regression)

The combined regression results in higher accuracy of the SUT parameter identification, but its efficiency depends on the previously applied fault detection and location method, which determines, which SVM module to run. If this method makes mistake, the SVM will also fail. However, this scheme is more efficient than the standalone regression, which has problems with processing whole data sets. In most cases the RBF function is the best choice, despite the time-consuming optimization process.

6. CONCLUSIONS

The paper presented the SVM regression method applied for monitoring the state of the induction machine. From two discussed approaches, the set of SVM modules activated by the preceding fault detection and location module is more efficient. However, it depends on the additional (for instance, classification) method. The approach activating all modules simultaneously works as standalone is simpler, but has small flexibility (greater MSE and only three usable kernels). The proposed method is more accurate than the classification of the motor states, but requires for that purpose larger training data sets. Further investigation requires introducing and comparing efficiency of additional kernels and checking the method for another systems.

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