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GSVD/LDA-BASED RVM SCHEME FOR FAULT DETECTION OF BROKEN ROTOR BARS IN INDUCTION MOTOR

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СХЕМА МЕТОДУ РЕЛЕВАНТНИХ ВЕКТОРІВ, ЗАСНОВАНА НА УЗАГАЛЬНЕНОМУ СИНГУЛЯРНОМУ РОЗКЛАДАННІ/ЛІНІЙНОМУ ДИСКРИМІНАНТНОМУ АНАЛІЗІ ДЛЯ ВИЯВЛЕННЯ НЕСПРАВНОСТЕЙ ЗУБЦІВ РОТОРА АСИНХРОННОГО ДВИГУНА

Purpose. Induction motors (IM) are the most important components in commercially available equipment and industrial processes. In this work, a framework based on the relevance vector machine (RVM) and generalized singular value decomposition/linear discriminant analysis (GSVD/LDA) used as fault detection of broken rotor bars (BRB) in IM is presented. We have obtained some important experimental results, which may become very helpful for the fault detection in induction motors.

Methodology. First, we used GSVD/LDA to reduce the dimension of stator current. Then the multiclass classifier as the fault diagnosis was decomposed into several binary RVM classifiers using One-vs-All method and their kernel parameters were determined through cross-validation.

Findings. By reducing the dimension of the current signal through GSVD/LDA, we lowered its redundancy significantly, so that the several binary RVM classifiers using One-vs-All method can perform better. The simulation results demonstrated that, the proposed method is more effective in identifying the fault of BRB in IM as compared with its counterpart.

Originality. We made a study of fault detection of broken rotor bars in induction motor by combining GSVD/LDA-based dimension reduction with the binary RVM classifiers using One-vs-All method. We verified its effectiveness through the simulation. We have not found previously-made researches on this aspect.

Practical value. The proposed method can be embedded in the fault diagnosis system of IM as a separate module. Since it shows the satisfactory accuracy, it can provide a reliable anchor for industrial and agricultural productions.

Keywords: *RVM, GSVD/LDA, induction motors, broken rotor bars, One-vs-All*

Introduction. Induction motors (IM), as a major source of power, are widely used in all types of industries because of their high reliability and robust design. However, they are subject to failures due to locked rotor, unbalanced supply voltage, overload, broken rotor bars and so on [1–3]. Therefore, the diagnosis of motor failures especially for broken rotor bars (BRB) is very important and needs to be highly accurate [4]. Various methods are applied for fault diagnosis of BRB in IM, some methods utilize the steady-state spectral components of the stator, these spectral components including current, voltage and power are often used to detect broken rotor bars. H. Douglas et al. [5] proposed a new method based on wavelet analysis; in this work, the startup transient current of IM was used as the medium for diagnoses; the fundamental component was extracted using an algorithm predicting the instantaneous amplitude and frequency during startup, and the residual current was then analysed using wavelets. J. Milimonfared et al. [6] found that, the motor was disconnected from the supply, and the induced voltage in the stator due to only rotor flux was utilized to detect the fault. Some pieces of literature have been summarizing the latest findings and trends in the field over the last decade with a number of survey papers, which has greatly promoted the technology development of fault diagnosis for BRB in IM [7–9].

The relevance vector machine (RVM), recently developed by Tipping [10], is a machine learning technique that uses Bayesian inference to obtain parsimonious solutions for regression and probabilistic classification. Like support vector machine (SVM) [11], it can efficiently deal a nonlinear classification by mapping samples from low dimensional space into high-dimensional space with a nonlinear kernel function. In this work, we proposed a framework based on RVM and GSVD/LDA used as fault detection of BRB in IM. We used GSVD/LDA to reduce the dimension of stator current, and then the multiclass classifier serving as fault diagnosis was decomposed into several binary RVM classifiers using One-vs-All method; and their kernel parameters were determined through cross-validation. The simulation results demonstrate the effectiveness of the proposed approach.

Fault characteristic of BRB. When the BRB faults of an induction motor occur, there is an increase in the current distribution in the two bars adjacent to the broken rotor bar; this causes an unbalanced air-gap local field and a modulated stator current. The frequency components, which are characteristic of BRB as a sequence of harmonics, are expressed as [12]

$$f_b = [(\frac{k}{p})(1-s) \pm s] f_0, k = 1, 2, \cdots$$

Here f_s is the supply frequency, p is the number of pole pairs, k is an integer and s is the rotor slip. When k=p the strongest harmonic will occur, and it will signify the lower sideband at $(1-2f)s$, the harmonic will generate torque and speed ripples at a frequency of $2sf$, it causes an upper sideband harmonic at $(1+2f)s$. Therefore, the additional component at frequencies around the fundamental induced by BRB is defined as

$$f_b = (1 \pm 2ks) f_0, k = 1, 2, \cdots .$$

Where f_0 is the fundamental frequency and s is the rotor slip. To express the IM stator current with broken bars, a simplified model containing additional current frequencies is given by

$$\begin{aligned} i(t) &= I_0 \cos(\omega_0 t - \varphi_0) + \\ &+ \sum_{k=1}^{N} I_{bpk} \cos[(1-2ks)\omega_0 t - \varphi_{bpk}] + \\ &+ \sum_{k=1}^{N} I_{bnk} \cos[(1+2ks)\omega_0 t - \varphi_{bnk}] + n(t). \end{aligned} \quad (1)$$

Where, I_0 is the fundamental current amplitude, I_{bpk} and I_{bnk} are the magnitudes of the left and the right additional components respectively, ω_0 is the angular frequency, φ_0 is the main phase shift, φ_{bpk} and φ_{bnk} are the initial phase angles of the left and the right additional components respectively, $n(t)$ is Gaussian noise with zero mean.

RVM for classification. Tipping [10] proposed the Relevance Vector Machine (RVM) to recast the main ideas behind SVM in a Bayesian context. For two classes classification, given a training dataset $\{x_n, t_n\}_{n=1}^{N}$, and the corresponding output is $t_n \in \{0,1\}$. The following classification model can be used to describe the mapping relation between the input pattern vector $\mathbf{x}$ and the output t

$$t_n = y(x_n, \mathbf{w}) + \varepsilon_n, \quad \mathbf{t} = \mathbf{y} + \boldsymbol{\varepsilon} . \quad (2)$$

Where the errors $\boldsymbol{\varepsilon} = (\varepsilon_1, ..., \varepsilon_n)$ are modeled probabilistically as independent zero-mean Gaussian, with variance σ^2, so $p(\varepsilon) = \prod_{n=1}^{N} N(\varepsilon_n | 0, \sigma^2)$, $\mathbf{w} = (w_1 ....., w_M)$ is the parameter vector and $y(x_n, \mathbf{w})$ can be expressed as a linearly weighted sum of some basis functions $\phi(\mathbf{x})$

$$y(\mathbf{x}, \mathbf{w}) = \sum_{m=1}^{M} w_m \phi_m(\mathbf{x}) + w_0, \quad \mathbf{y} = \Phi \mathbf{w} .$$

Here $\Phi = [\phi_1, \cdots, \phi_M]$ is the N×M design matrix whose columns comprise the complete set of M basis vectors. Note that the form of the function (2) is equal to the form of the function for a SVM, where we identify our general basis functions with the kernel as parameterized with the training vectors

$$\phi_m(\mathbf{x}) = K(\mathbf{x}, x_m) \text{ and } \phi(x_n) = [1, K(x_1, x_n), ...K(x_N, x_n)],$$

when classify $y(x|w)$ the Sigmoid function is used as

$$p(t_i = 1 | w) = \sigma[y(x_i; w)] = \frac{1}{1+e^{-y(x_i; w)}} .$$

Then the Likelihood function is obtained as

$$p(t|w) = \prod_{i=1}^{N} \sigma[y(x_i; w)]^{t_i} (1 - \sigma[y(x_i; w)])^{1-t_i} .$$

Using the Laplace approximation, and for a fixed value of α, the mode of the posterior distribution over w is obtained by maximizing

$$\begin{aligned} w_{MP} &= \arg\max_{w} p(w | t, a) = \\ &= \arg\max_{w} \frac{p(t|w) p(w|a) p(a)}{p(\alpha, t)} = \\ &= \arg\max_{w} p(t|w) p(w|a) = \\ &= \arg\max_{w} \log(p(t|w) p(w|a)) . \end{aligned}$$

Its Logarithmic likelihood function is

$$\begin{aligned} &\log(p(t|w) p(w|a)) = \\ &= \sum_{i=1}^{N} [t_i log y_i + (1-t_i) log(1-y_i)] - 0.5 w^T A w . \end{aligned}$$

The mode and variance of the Laplace approximation for w are

$$\begin{cases} w_{MP} = \Sigma_{MP} \Phi^T B \mathbf{t} \\ \Sigma_{MP} = \left(A + \sigma^{-2} \Phi^T \Phi\right)^{-1} \end{cases} .$$

Where B is N×N diagonal matrix with b_{nn}=$f(x_n;w)(1$-$f(x_n;w))$, the marginal likelihood is

$$p(t|x,a) = \int p(t|x,w)pw|a)dw =$$
$$= p(t|x,w_{MP})p(w_{MP}|a)(2\pi)^{M/2}\,|\,\Sigma_{MP}\,|^{1/2}\,.$$

When maximizing the above equation with respect to each α_i, one eventually obtains

$$\begin{cases} a_i^{new} = \dfrac{\gamma^i}{\mu_i^2} \\ (\sigma^2)^{new} = \dfrac{\|t-\Phi\mu\|^2}{N = \sum_{i=0}^{N}\alpha_i\Sigma_{i,i}} \end{cases}.$$

LDA/GSVD. LDA/GSVD based on Fisher linear discrimination analysis and the theory of generalized singular value decomposition is used as feature dimension reduction to the singular data space, it can effectively avoid the calculation about any data set between the between-class scatter matrix and the within-class scatter matrix, thus solving the small sample problem.

Suppose a data set of n data vectors in n-dimensional space is denoted as

$$A = \{x_1, x_2, \cdots, x_N \in R^d\} = \bigcup_{j=1}^{c} A_j\,.$$

Where c is number of classes, and each subclass A_j has n_j samples and $d \le c$.The between-class scatter matrix and the within-class scatter matrix are respectively defined as

$$S_B = \sum_{k=1}^{c} n_k\,(\mu_k - \mu)(\mu_k - \mu)^T\,;$$
$$S_W = \sum_{k=1}^{c}\sum_{x_i \in A_k}(x_i - \mu_k)(x_i - \mu_k)^T\,.$$

Where $\mu_k = \frac{1}{n_k}\sum_{x_i \in A_k} x_i$ and $\mu = \frac{1}{c}\sum_{k=1}^{c}\mu_k$ are the centroid of the ith class and the global centroid respectively, then we define

$$H_B = [\sqrt{n_1}\,(\mu_1 - \mu), \sqrt{n_2}\,(\mu_2 - \mu), \cdots, \sqrt{n_c}\,(\mu_c - \mu)]\;;$$
$$H_W = [A_1 - \mu_1 e_1^T, A_2 - \mu_2 e_2^T, \cdots, A_c - \mu_c e_c^T]\,.$$

Here $e_k = [1,1,\cdots,1] \in R^{c_k \times 1}$, then we have: $S_B = H_B H_B^T$ and $S_W = H_W H_W^T$, so we obtain

$$U^T H_B X = diag(a_1, a_2, \cdots, a_m)\,;$$

$$V^T H_W X = diag(\beta_1, \beta_2, \cdots, \beta_m)\,.$$

Where U and V are orthogonal respectively, X is nonsingular.

The procedure of LDA/GSVD is described as follows:

1. Compute S_B and S_W, then define $J(w) = \dfrac{w^T S_B w}{w^T S_W w}$.

2. According to equation H_B and H_W, then define $K = [H_B, H_W]^T$, and compute its singular value decomposition $P^T K^T Q = \begin{bmatrix} R & 0 \\ 0 & 0 \end{bmatrix}$.

3. Let $t = rank(K)$ and compute the SVD of $P(1:c,1:t)$ which is $U^T P(1:c,1:t)W = \sum_a$.

4. Compute $X = Q\begin{bmatrix} R^{-1}W & 0 \\ 0 & I \end{bmatrix}$ and $W_{opt} = X(1:m, 1:c-1)$.

5. For a high dimension sample $x_N \in R^d$, the new reduced-dimension feature is expressed as

$$y = W_{opt}^T x\,.$$

Simulation results. To evaluate the performance of the proposed method, a numerical simulation has been performed. This signal is similar to the measured current for three broken bars at rated load. We use the equation (1) to generate this signal, and the corresponding parameters are set as $I_0 = 5\text{A}$, $I_{bpk} = 0.08\text{A}$, $I_{bnk} = 0.061\text{A}$, $\omega_0 = 100\pi$, $\varphi_0 = \pi/4$, $\varphi_{bpk} = \pi/3$, $\varphi_{bnk} = \pi/6$, $s = 0.024$, $N = 1,2,3,4$, the sampling frequency is 250 Hz and the sampling length is 1024.

The objective of the fault diagnosis of BRB in IM is to develop classifiers that are able to identify any input combination as belonging to one of the different fault classes. For developing the proposed classifier, there are five different fault conditions including normal, *1* broken bar, *2* broken bars, *3* broken bars and *4* broken bars, each of which contains 30 samples, so a total of 150 samples as a data set is used to the classifier. 100 examples are randomly taken from each fault condition of the data set and used for training the classifier, the rest are used for testing.

The time domain waveform of each fault condition and its corresponding spectrogram diagram is illustrated in Fig. 1–5. We use GSVD/LDA to reduce dimension for 100 training samples. Fig. 6 shows the feature vector of the reduced-dimension training samples, it can be seen that the first *4* feature vector components are not equal to 0, and the rest are almost 0, moreover, the between-class scatter is very large and the within-class scatter is very small, thus it will effectively improve the classification accuracy of the classifier.

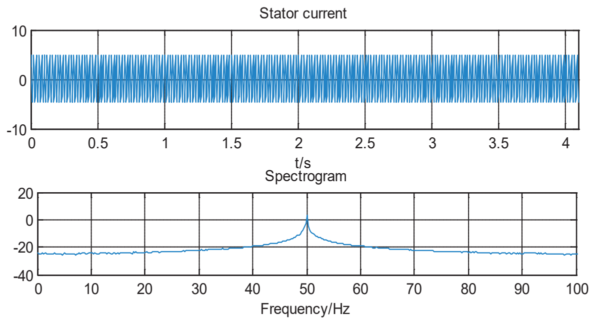

Fig. 1. Normal condition

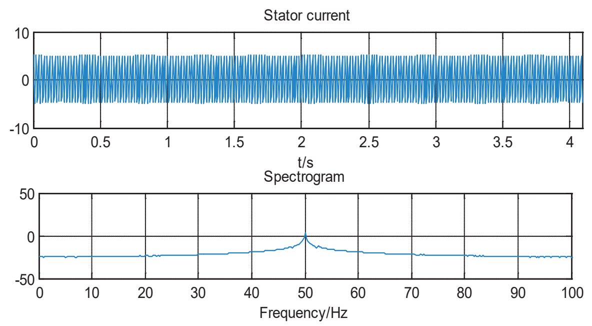

Fig. 2. 1 broken bar condition

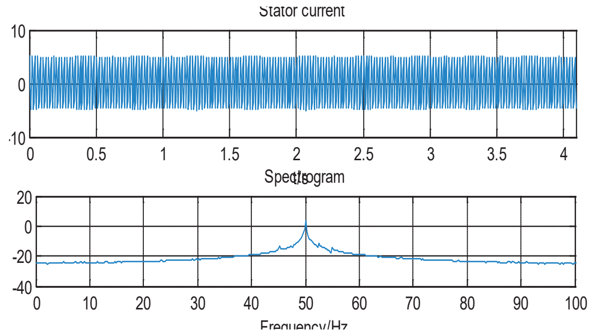

Fig. 3. 2 broken bars condition

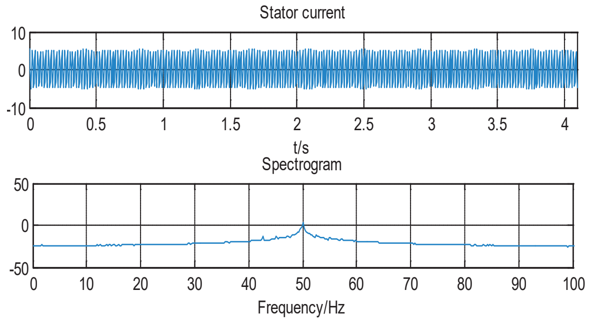

Fig. 4. 3 broken bars condition

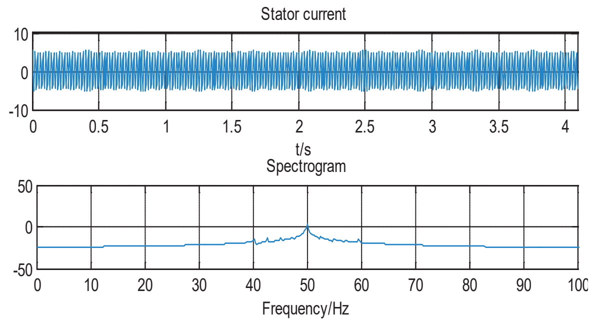

Fig. 5. 4 broken bars condition

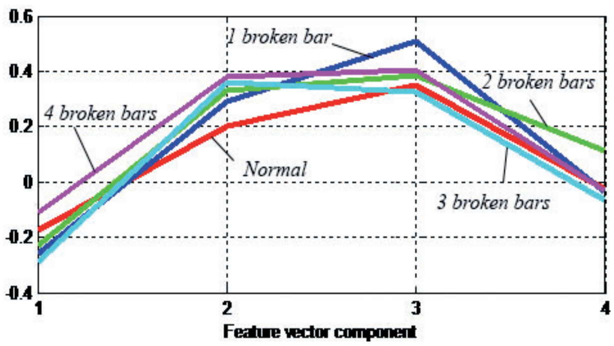

Fig. 6. Feature vector component of reduced-dimension training samples

The fault diagnosis of BRB is taken as a multiclass classification problem, which can be decomposed into several binary classification problems; and they can be solved efficiently using binary classifiers. In this work, we use One-vs-All approach to deal the decomposition for the multiclass classification problem. It reduces the multiclass problem among 5 classes into 5 binary problems, in which each problem discriminates a given class from the other 4 classes, with the samples of that class as positive samples and all other samples as negative. Then these binary classifiers are tested using the training samples, this strategy enables each binary classifyer to produce a real-valued confidence score for its decision. The real-valued output is considered the winner, and this class label is assigned to that example, when the binary classifier is tuned well. This simple method will provide a good classification accuracy, which can match many other more complicated multiclass classification approaches. For the binary classifiers, the Gaussian kernel is used as the kernel function of RVM, there is one parameter to be determined which plays a critical role in the performance of RVM, the appropriate selection for kernel parameter may cause its sparsity and accuracy. For this binary classifiers, we use 10-fold cross-validation to investigate the appropriate kernel parameter, each kernel parameter is tried and the one with the best cross-validation accuracy is selected. After that, the classifier is trained through all the training samples once more to obtain the optimal classifier using the best kernel parameter.

For the comparison, we get the feature vectors by using feature extraction methods GSVD/LDA and PCA and the training processes are carried out using PCA-RVM, GSVD/LDA-RVM, after that, the two classifiers are applied to the test samples. With the decrease of the dimension of samples, the number of support vectors also decreases. The comparison results between the two classifiers are shown in the table. It can be seen that from table, the classification rate with GSVD /LDA-RVM is highest, and it can always perform better than PCA-RVM for both training results and test results, when the representative training samples is enough, a Bayesian optimal multiclass classifier must be obtained. For the simulation model, there are not other components that can generate some particular frequencies and noise interfering with the model data, so the accuracy of all the classifiers is relatively high.

Table

Comparison of the Results
Received by the Two Methods

Method	Training accuracy	Testing accuracy
GSVD/LDA-RVM	100%	100%
PCA-RVM	99%	98%

Conclusions. It is important to choose an appropriate and effective approach to diagnose the BRB faults in IM. This paper presents the hybrid framework based on RVM and GSVD/LDA used for BRB faults detection. In this framework, GSVD /LDA reduced the dimension of stator current, and then the multiclass classifier used as fault diagnosis was decomposed into several binary RVM classifiers using One-vs-All method and their kernel parameters were determined through cross-validation.The simulation results clearly demonstrate that the proposed method is a promising method of the faults diagnosis, which detects BRB in IM.

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Мета. Асинхронний електродвигун є найбільш важливою складовою устаткування, що серійно випускається, і виробничих процесів. У представленій роботі метод релевантних векторів, заснований на узагальненому сингулярному розкладанні/лінійному дискримінантному аналізі, використаний для виявлення несправностей стрижнів ротора асинхронного двигуна. Дані, отримані нами в результаті експериментів, можуть виявитися дуже корисними для виявлення несправностей стрижнів ротора асинхронного двигуна.

Методика. На первинному етапі узагальнене сингулярне розкладання/лінійний дискримінантний аналіз використовуються для зменшення розмірності масиву струму статора. Потім поліноміальний класифікатор, застосований для виявлення несправностей, був розкладений на декілька бінарних класифікаторів за методом релевантних векторів, в яких використовувався підхід „один проти всіх", а їх базові (основні) параметри визначаються шляхом перехресної перевірки.

Результати. Завдяки зменшенню розмірності струмового сигналу методом узагальненого сингулярного розкладання/лінійного дискримінантного аналізу значно знижується надмірність сигналу, що підвищує ефективність бінарних класифікаторів, складених за методом релевантних векторів, що використовує підхід „один проти всіх". Результати моделювання показали, що запропонований метод виявлення несправностей стрижнів ротора асинхронного двигуна ефективніший, ніж його аналоги.

Наукова новизна. Вивчений процес виявлення несправностей стрижнів ротора асинхронного двигуна, в якому поєднуються методи зменшення розмірності струму статора шляхом узагальненого сингулярного розкладання/лінійного дискримінантного аналізу й бінарних класифікаторів за методом релевантних векторів, в яких використовувався підхід „один проти всіх". Ефективність методу підтверджена методом моделювання. Дослідження даного аспекту раніше не проводилися.

Практична значимість. Запропонований метод може бути запроваджений до системи діагностики несправностей асинхронних двигунів як окремий модуль. Оскільки він має задовільну точність, він може надійно закріпитися у промисловому та сільськогосподарському виробництві.

Ключові слова: *метод релевантних векторів, узагальнене сингулярне розкладання/лінійний дискримінантний аналіз, асинхронний електродвигун, несправний стрижень ротора, підхід „один проти всіх"*

Цель. Асинхронный электродвигатель является наиболее важной составляющей серийно выпускаемого оборудования и производственных процессов. В представленной работе метод релевантных векторов, основанный на обобщенном сингулярном разложении/линейном дискриминантном анализе, использован для обнаружения неисправностей стержней ротора асинхронного двигателя. Данные, полученные нами в результате экспериментов, могут оказаться очень полезными для обнаружения неисправностей стержней ротора асинхронного двигателя.

Методика. На первоначальном этапе обобщенное сингулярное разложение/линейный дискриминантный анализ используются для уменьшения размерности массива тока статора. Затем полиномиальный классификатор, применяемый для выявления неисправностей, был разложен на несколько бинарных классификаторов по методу релевантных векторов, в которых использовался подход „один против всех“, а их базовые (основные) параметры определяются путем перекрестной проверки.

Результаты. Благодаря уменьшению размерности токового сигнала методом обобщенного сингулярного разложения/линейного дискриминантного анализа значительно снижается избыточность сигнала, что повышает эффективность бинарных классификаторов, составленных по методу релевантных векторов, использующим подход „один против всех“. Результаты моделирования показали, что предложенный метод обнаружения неисправностей стержней ротора асинхронного двигателя более эффективен, чем его аналоги.

Научная новизна. Изучен процесс выявления неисправностей стержней ротора асинхронного двигателя, в котором сочетаются методы уменьшения размерности тока статора путем обобщенного сингулярного разложения/линейного дискриминантного анализа и бинарных классификаторов по методу релевантных векторов, в которых использовался подход „один против всех“. Эффективность метода подтверждена методом моделирования. Исследования данного аспекта ранее не проводились.

Практическая значимость. Предложенный метод может быть внедрен в систему диагностики неисправностей асинхронных двигателей в качестве отдельного модуля. Поскольку он обладает удовлетворительной точностью, он может надежно закрепиться в промышленном и сельскохозяйственном производстве.

Ключевые слова: *метод релевантных векторов, обобщенное сингулярное разложение/линейный дискриминантный анализ, асинхронный электродвигатель, неисправный стержень ротора, подход „один против всех“*

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