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Optimal Rotor Fault Detection in Induction Motor Using Particle-Swarm Optimization Optimized Neural Network

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ABSTRACT

This study examined and presents an effective method for detection of failure of conductor bars in the winding of rotor of induction motor in low load conditions using neural networks of radial-base functions. The proposed method used Hilbert method to obtain the stator current signal push. The frequency and signal amplitude of the push stator were used as the input of the neural network and the network outputs were rotor fault state, and the number of conductive bars with broken fault. Moreover, particle-swarm optimization algorithm was used to determine the optimal network weights and neuron penetration radius in the neural network. The results obtained from the proposed method showed the optimal and efficient performance of the method in detecting conductive bars broken fault in induction motor in low load conditions.

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1. INTRODUCTION

Today, the issue of monitoring and maintaining the induction motor is very important given the widespread use of these motors in various transportation, aviation, and home industries. One of the most important and prominent methods in maintenance of induction motors is the issue of detection of faults in these motors, which leads to more reliability of the system. Induction motor faults are due to mechanical and electrical events [1]. Mechanical factors are usually related to overloads and sudden changes in load that can cause bearing faults and breakage of the rotor bar. Electrical factors are generally dependent on source power [2].

Among the cases where monitoring is necessary; when the rotor bars of the induction motor break down. In this case, the current passing through the broken- bar becomesvery low and the current of the bars around the broken bar increases [3]. Sometimes this increase in the current causes the melting of the bars and the emission of faults and temperature rise, as well as the creation of an electric arc in the induction motor and ultimately leads to the loss of the rotor. Thus, the problem of trouble shooting of breakingfault of the rotor bars of the induction motor is of particular importance [4].

So far, various studies have been conducted on detection of faults in motor rotors. In literature [5], the detection of the rotor break fault of a permanent magnet synchronous motor was dealt using random forest classification method. One of the most practical methods used to detect faults in induction motors is Hilbert transform. Fault locating in the induction motor rotor using push signal analysis [6], detecting the presence of broken rotor bars [7], fault detection in the induction motor by rotational deviation technique [8], and multi-class fault diagnosis scheme for induction motor [9] are some applications of Hilbert transform. If the conductive bars in the rotor's winding become faulty (breakage or outage), both geometrically and magnetically, the motor will suffer imbalance, which will create harmonics in the stator current range. These harmonics are proportional to $(1 \pm 2ks)f$ frequencies, where f is the base frequency, s is the slip and k=1, 2, 3. Thus, by analyzing these frequencies and the amplitude of these harmonics, one can diagnose the state of the fault occurred in the rotor conductor bars. However, at small slips, these harmonics are near base frequencies,

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so it is difficult to detect them. Nonetheless, it is possible to detect the effect of the rotor fault by using the field domain of the oscillator signal's frequency amplitude. This fault is related to the frequency component 2sf [10, 11]. Neural network of the radial base functions will be used to analyze this signal and to determine the status of the rotor fault in this paper. As neural networks are very effective and flexible in solving nonlinear and complex structures, and do not need an accurate mathematical model of the system to identify faults, great attention has been paid to their use in detecting and detecting faults in various systems, specially engines [10-13].

This paper proposed a method to improve the fault detection function of an induction motor rotor in low load conditions, which will be based on the Hilbert transform and neural network and the radial base function optimized with the particle-swarm optimization algorithm. Hilbert transform is used to extract the push signals of stator current, and then to extract the fault component from the push signal of the stator current, 2sf harmonic position, and its amplitude will be used as input to the neural network. In addition, particle-swarm optimization algorithm will be used to determine the-optimal network weights and neuronpenetration radius in the neural network. In the process of presenting the paper, the first step is to introduce and investigate the induction motor equations as well as the analysis of the-stator current flow. In the third section, we will investigate the neural network to detect the stator state and the particle-swarm optimization algorithm. Section 4 presents the results of this study. The main idea and the nevelty of this work is to create an optimal neural network and perform- optimization on the system and anerro r detection method, such as finding optimal pparameters, optimizing the error detection procedure, and avoiding the determination of parameters by manual methods.

2. ANALYSIS OF PUSH CURRENT STATOR

2. 1. Dynamic Model of Induction Motor with Faulty Rotor

Figure 1 shows the diagram of the induction motor circuit, in which the broken conductor bars are modeled with the equivalent resistance on the base d-q. Accordingly, themathematical model of the three-phase induction motor on thee base d-q and relative to the rotor's side is as follows [14]:

$$\dot{x}(t) = A(\omega)x(t) + Bu(t)$$
$$y(t) = Cx(t) \tag{1}$$

$$x = \begin{bmatrix} i_{ds} & i_{qs} & \phi_{dr} & \phi_{qr} \end{bmatrix}$$
$$\mathrm{u} = \begin{bmatrix} \mathrm{U_{ds}} \\ \mathrm{U_{qs}} \end{bmatrix}.\ \mathrm{y} = \begin{bmatrix} \mathrm{i_{ds}} \\ \mathrm{i_{qs}} \end{bmatrix} \tag{2}$$

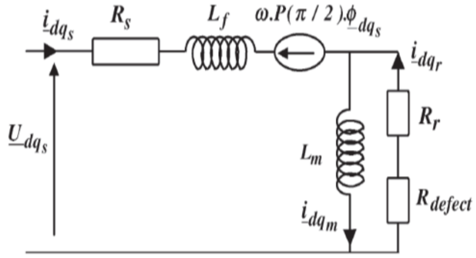

Figure 1. The model of induction motor with faulty rotor [14]

$$A(\omega) = \begin{bmatrix} -(\mathrm{R_s}+\mathrm{R_{eq}})\mathrm{L_f^{-1}} & \omega_\mathrm{r} & \mathrm{R_{eq}L_m^{-1}L_f^{-1}} & \omega_\mathrm{r}\mathrm{L_f^{-1}} \\ -\omega_\mathrm{r} & -(\mathrm{R_s}+\mathrm{R_{eq}})\mathrm{L_f^{-1}} & \omega_\mathrm{r}\mathrm{L_f^{-1}} & \mathrm{R_{eq}L_m^{-1}L_f^{-1}} \\ \mathrm{R_{eq}} & 0 & \mathrm{R_{eq}L_m^{-1}} & 0 \\ 0 & \mathrm{R_{eq}} & 0 & -\mathrm{R_{eq}L_m^{-1}} \end{bmatrix} \tag{3}$$

$$B = \begin{bmatrix} L_f^{-1} & 0 \\ 0 & L_f^{-1} \\ 0 & 0 \\ 0 & 0 \end{bmatrix} ;\ C\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \tag{4}$$

And R_{eq} equals:

$$R_{eq} = R_r + \frac{a}{1-a}Q(\theta_0)R_r \tag{5}$$

Here, θ_0 shows the faulty winding position (broken conductor bars of rotor) relative to the first phase of therotor. This parameter can be 0, $\frac{2\pi}{3}$ or $\frac{2\pi}{4}$, depending on-whether the faulty winding is in phase a, b, or c from the rotor, respectively. Matrix Q (θ_0) is as follows:

$$Q(\theta_0) = \begin{bmatrix} \cos^2(\theta_0) & \cos(\theta_0)\sin(\theta_0) \\ \cos(\theta_0)\sin(\theta_0) & sin^2(\theta_0) \end{bmatrix}$$
$$a = \frac{2}{3}\eta_0 \,.\, \eta_0 = \frac{3n_{bc}}{n_b} \tag{6}$$

In Equation (6), parameter η_0 shows the ratio of the faulty conductor bar (n_{bc}) to all conductor bars (n_b) in the rotor. ω_r is the mechanical speed of the rotor, which can be linkedto the state variables by means of the following equations:

$$\dot{\omega}_r = \frac{1}{J_r}(T_{em} - T_L)$$
$$T_e = p(i_{qs}\phi_{dr} - i_{ds}\phi_{qr}) \tag{7}$$

In the above equations, T_{em} is the electromagnetic torque,T_L is the torque load (mechanical torque), J_r is the torque of rotor inertia with the load, and p is the number of poles.

2. 2. Signal Push of Stator Phase Current

As the real signals are non-stationary and non-linear, signal analysis methods must be able to adjust themselves with the signal. Among the many methods of signal analysis, Hilbert transform is one of the most important and efficient methods. Hilbert transform creates a mixed signal, the real part of which is the main signal and its fictional part is Hilbert signal transform [15].

In this study, Hilbert transform is used for a real signal x(t), such as phase current, to extract the local features of that signal. From the mathematical point of view, Hilbert transform of the signal x(t) is defined as the convolution of the x(t) signal with the function 1 / t as follows:

$$\mathrm{HT}\ \left(\mathrm{x(t)}\right) = \mathrm{y(t)} = \frac{1}{\pi \mathrm{t}} * \mathrm{x(t)} = \frac{1}{\pi}\int_{-\infty}^{+\infty} \frac{\mathrm{x(t)}}{\mathrm{t}-\tau} d\tau \quad (8)$$

By coupling the signal x(t) to its Hilbert transform, the following signal, as the analytical signal x(t), is generated.

$$\vec{x}(t) = x(t) + jy(t) = a(t)e^{j\theta(t)} \quad (9)$$

Here, $a(t) = \sqrt{x^2(t) + y^2(t)}$. a(t) is the moment domain of $\vec{x}(t)$, which can provide an image of how to change the energy of the signal x(t) relative to time. θ(t) is the momentary phase of the signal $\vec{x}(t)$ ،and $|a(t)|$is the push signal x (t).

3. DETECTING STATOR STATUS

3. 1. Particle-Swarm Optimization Algorithm

Particle-swarm optimization algorithm was first introduced as a local movement model for a group of animals [16] and includes a swarm of particles, each of which can be an optimal response for the problem being optimized.

The algorithm continuously updates the position of each particle by calculating the particle velocity and its application to the particle position. If $x_i(t)$ is the position of the particle i intime t, the position of the particle at any time will be equal to:

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (10)$$

The algorithm repeatedly updates the position of each particle by calculating the particle velocity and its application to the particle position. If xi (t) is the position of the i-th particle at time t, the position of the particle at any time will be equal to:

$$\begin{aligned} v_{i.j}(t+1) &= \omega v_{i.j}(t) \\ &+ c_1 r_{1.j}\left[y_{i.j}(t) - x_{i.j}(t)\right] \quad (11) \\ &+ c_2 r_{2.j}\left[\hat{y}_j(t) - x_{i.j}(t)\right] \end{aligned}$$

The structure of the algorithm is in such a way that all particles are fully interconnected. In each time cycle, all particles are updated with the position of the best particle in the whole particle. The velocity equation is as follows. Here $v_{i.j}(t)$is the velocity of the particle i in the dimension j at time t. The velocity density is ω_i and the constants c_1 and c_2 are coefficients of velocity.

3. 2. Neural Network to Detect Rotor Status

In this study, the neural network of radial base function was used to analyze the stator current push signal and to determine the status of the rotor fault. The first step in using a neural network is the use of a series of training data that uses the neural network to learn. There are several ways to train a neural network that can be divided into general, supervised, and unsupervised methods. In the supervised methods, the training data are as input-output data pair (X-Y_d). Thus, for X input, the optimal output Y_d is available and the target is to find the mapping between the input and the output. In unsupervised training mode, the input data X is available only together with a cost function and the purpose is to find a mapping of X, so that that cost function is minimized.

In supervised training, the cost function canbe the sum of the squares of the error between input and output on the pair of training data. In this paper, the supervised method is used as the input and output pairs are available. The pair of training data is selected as follows:

1. Neural Network input: Push signal specifications of the stator current.
2. Neural network output: Rotor faults status (the number of conducting bars with fault in the rotor).

The mentioned training data is generated using the dynamic model of the induction motor with a faulty rotor. The neural network is intended to detect the rotor's state with 12 neurons in the hidden layer according to Figure 3. In Figure 3, the input of the neural network is two- dimensional vector $x = [x_1 \quad x_2]^T$, and y output will be a scalar with values 1 to 3. The functions f_i *(x)* as activation functions of the neurons are all considered as Gaussian.

$$f_i(x) = e^{-\left(\frac{\|x-m_i\|}{\sigma_i}\right)^2} \quad (12)$$

In the above equation, m_i is a two-dimensional vector representing the center of the Gaussian function f_i, the scalar parameter σ_i is the radius of neuron penetration and w_i is the weights of the neural network. The neuron outputs are added up and form the final output of the neural network y after weighed by w_i. By specifying the parameters w_i, σ_i and mi, the neural network can fully be defined.

4. SIMULATION RESULTS

The motor examined in this paper is an induction motor 50Hz, 220v, 4-pole with a nominal power of 1.1kW, and the number of rotor conductor bars is n_b= 28. The parameters of the induction motor system are presented in Table 1. The stator phase current signal (for an axis at d-q base) with its push and the signal strength spectrum will be like Figure 4. By changing the number of faulty bars or torque load T_L the location and harmonic amplitude of 2sf frequency will change.

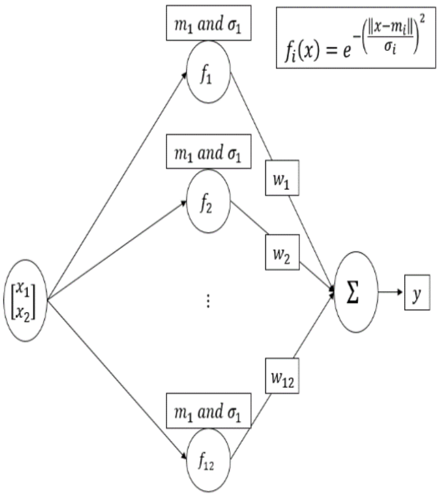

Figure 3. RBFN neural network with 12 neurons in the hidden layer to detect the rotor status [17, 18]

TABLE 1. Induction Motor Engine Parameter

Parameter	**The amount of**
Output power (P_{out})	1.1 kW
Stator Voltage (V_s)	220/380 V
Stator nominal current (I_s)	2.6/4.3 A
Stator nominal velocity(n)	425 rpm
Rotor resistance (R_r)	3.83 Ω
Stator resistance (R_s)	9.81 Ω
Coupling inductance (L_m)	436 mH
Stator leak inductance (L_f)	76.2 mH
Number of rotor conductor rods (n_b)	28

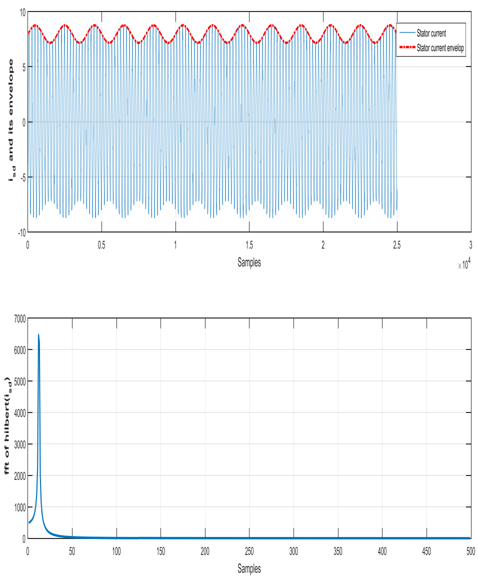

Figure 4. (a) signal of stator current with its push, (b) push signal power spectrum

As already mentioned, in this research, the amplitude and frequency of the harmonic 2sf in the stator phase current-signal strength spectrum are the inputs of theneural network and the output is the status of the rotor barsis the number of broken bars. Thus, by changing the parameters of the torque load T_L and the number of broken conductor bars, and observing the status of the stator phase current-signal power spectrum, the training data for the training of the neural network will be generated. As seen in Figure (b-4), the neural network is trained with 500 training data.

The horizontal axis in Figure 5 shows the number of pairs of training data. Figure 5 (a) shows the harmonic amplitude of the 2sf in the stator voltage current signal strength spectrum. The above data varies in quadruple categories associated with different load torques and the number of broken conductors. The data of Figure 5 are shown in Table 2.

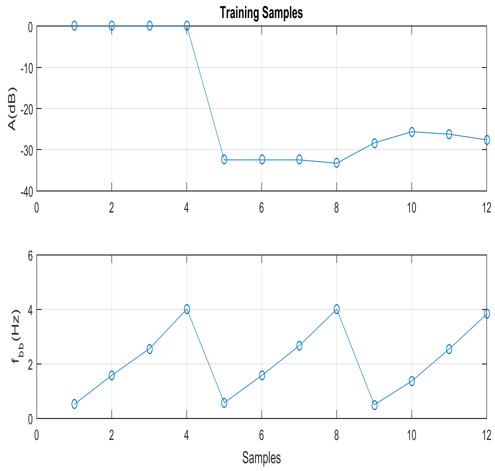

Figure 5. Training data for training the neural network

TABLE 2. Educational data for the neural network

Neural network input (two-dimensional)		**Neural network output (one-dimensional)**
A(dB)	**$x_1 f_{bb}$(Hz)**	**$x_2 y$**
0	0.515	1
0	1.5781	
0	2.55	1
0	4.007	1
-32.48	0.571	2
-32.48	1.571	2
-32.48	2.664	2
-33.3	4	2
-28.34	0.493 3	
-25.64	1.364	3
-26.24	2.542	3
-27.61	3.821	3

In Table 2, y = 1 means flawless rotor y = 2 means a rotor with a broken bar and y = 3 corresponds to a rotor with two broken bars. Neural network neurons center, i.e. m_i vector is considered the training inputs in Table 2, but σ_i and W_i were obtained using PSO method. Thus, the vector of optimization variables in PSO algorithm will be a vector with 24 elements, of which the 12 first elements are related to the weights W_i and the 12 second are related to σ_i. The parameters of PSO algorithm are considered as $c_1 = c_2 = 1.4962$, $\omega = 0.7298$ [19].

The PSO algorithm cost function is also the sum of the absolute magnitude of the error on all training data and is considered as follows:

$$J_{cost} = \sum_{k=1}^{12} |e_k|. \quad e_k = y_d - y \tag{13}$$

In Equation (13), y_d for k = 1,2, ..., 12 is the same data from rows 1 to 12 related to column y in the table. The method of changing the cost function by PSO algorithm is shown in Figure 6.

As shown in Figure 6, after 1000 sages of generation production, optimization with PSO algorithm has reached the value of the cost function j_{min} = 0.0883. Weight variations in the optimization process are shown in Figure 7.

As shown in Figure 7, weights have converged to constant values. The final values of these weights are placed in the neural network and the network is evaluated for both training data and experimental data. The changes in the neuron neuronal penetration radii in the optimization process are shown in Figure 8.

As shown in Figure 8, the penetration radii converge toconstant values. In Figure 9, the results of the detection of the rotor status, which is obtained by the neural network according to the training data, were compared with the main values. As seen, the neural network has detected the high accuracy of the rotor's state.

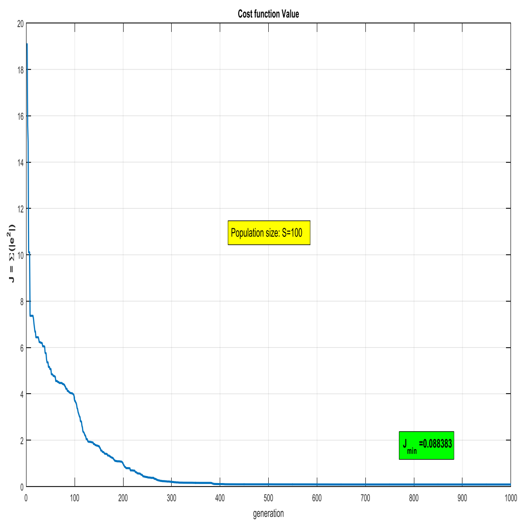

Figure 6. Variations in cost function (Total sum of absolute faults on training data) by PSO optimization process

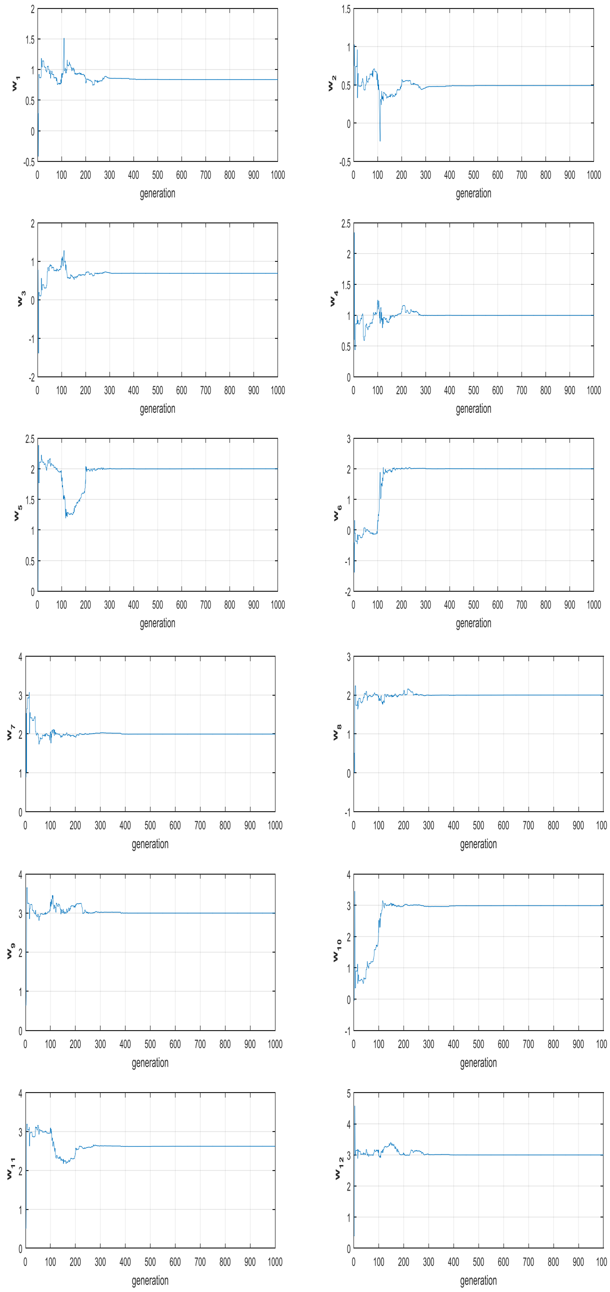

Figure 7. Variations in neural network weights in the optimization process

It is worth noting that in addition to the training data, the neural network must also be correct for experimental data that falls within the training data range. In doing so, select a couple of experimental dataset are selected, the neural network obtained for them is tested, and the results were compared with the original results.

Figure10 shows the curve for experimental data, and the results obtained from the neural network are shown in Figure 11. As seen, the desired neural network has been able to detect the rotor's position for experimental data correctly and accurately.

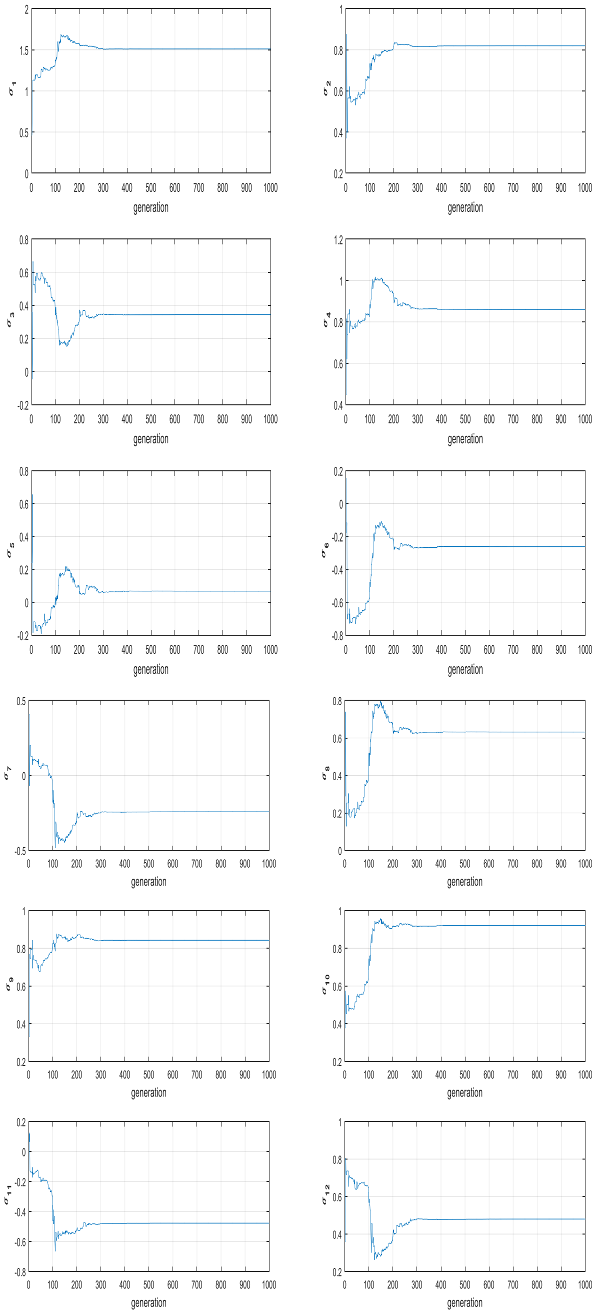

Figure 8. The changes in the neuron neuronal penetration radii in the optimization process

5. CONCLUSIONS

This paper examined an effective and precise method for determining the breakage fault of rotor bars of the induction motor in low load conditions. In order to improve the error detection process, Hilbert transform was used to extract the stator current signal. Neural network inputs are radial based function, 2sf harmonic position and its amplitude. Moreover, to improve and optimize the performance of the neural network, PSO algorithm was used to find optimal network weights and neuron penetration radii. The results obtained show the exact and desirable performance of the proposed method in determining the number of broken rotors in the induction motor.

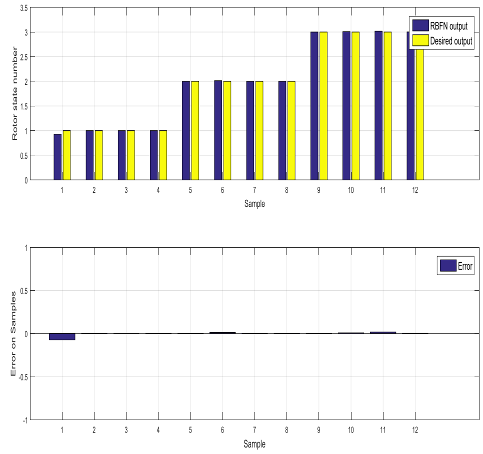

Figure 9. Neural network evaluation and its results compared with the real results for the training data

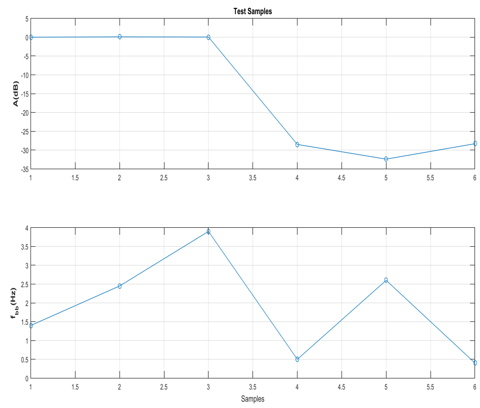

Figure 10. Training data for testing the neural network

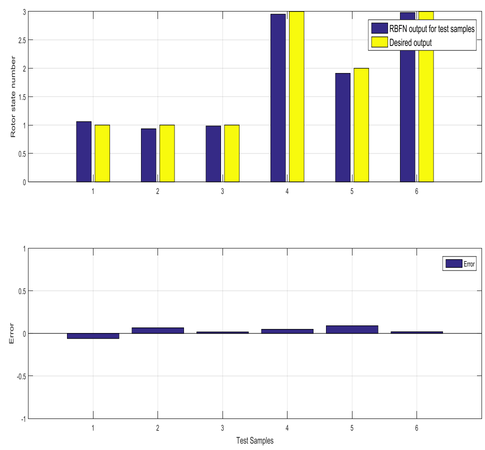

Figure 11. Results from the neural network versus Original results for experimental data

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Optimal Rotor Fault Detection in Induction Motor Using Particle-Swarm Optimization Optimized Neural Network

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چکیده

دراین پروژه شبه ارائه و بررسی یک روش مؤثرجهت شناسایی شکستگی میله‌های رسانا در سیم‌پیچی روتور موتور القایی در شرایط بار کم با استفاده از شبکه‌های عصبی توابع پایه شعاعی پرداخته شده است. در این روش پیشنهادی جهت بدست آوردن پوش سیگنال جریان استاتور از هیلبرت استفاده شده است. از فرکانس و دامنه سیگنال پوش استاتور بعنوان ورودی شبکه عصبی استفاده شده و خروجی شبکه وضعیت خطای روتور، تعداد میله‌های رسانای دارای خطای شکستگی، می‌باشد. همچنین از الگوریتم بهینه‌سازی انبوه ذرات جهت تعیین بهینه وزن‌های شبکه و شعاع نفوذ نرون در شبکه عصبی استفاده شده است. نتایج بدست آمده از روش پیشنهادی نشان‌دهنده عملکرد مطلوب و کارآمد روش در جهت تشخیص خطای شکستگی میله‌های رسانا در روتور موتور القایی در شرایط بار کم می‌باشد.

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