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Intelligent Determining Amount of Inter-Turn Stator Winding Fault in Permanent Magnet Synchronous Motor Using an Artificial Neural Network Trained by Improved Gravitational Search Algorithm

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Abstract

Extension of inter-turn fault in windings of PMSM can damage all parts of electrical systems, and in some cases in sensitive applications may lead to irreparable events. Identification of such small faults at incipient steps can be so helpful to protect entire part of electrical system. In this paper, intelligent protection system is designed which is made by two major parts. In the first part of intelligent protection system K-Nearest Neighbor classifier is used as a detecting system to discriminate inter-turn fault from normal condition, phase to phase fault and open circuit condition and also to detect faulty phase, simultaneity. After that if inter-turn fault is happened, second part of proposed system which is based on an ANN Trained with Improved Gravitational Search Algorithm determines the amount of fault. IGSA is presented to improve the performance of the proposed protection system in this paper. Obtained results show that both part of intelligent proposed and intelligent protection system can do their best performance. It can successfully detect inter-turn fault and follow it and predict amount of this fault.

Keywords: *population optimization algorithm, gravitational search algorithm, RMS value of current, negative sequence current, inter-turn stator winding fault, permanent magnet synchronous motor*

1. Introduction

The history of the identification faults in electric machines is as old as the electric machines. Initially, manufacturers and consumers relied on simple protection systems, such as Over Current, Over Voltage, Earth-Fault and etc. But today, since the demands for these machines have been increased and in other hand they are used in critical applications, it does seem necessary to design the fast and accurate systems that can quickly and with minimum delay detect faults in early steps [1]. However fault detection methods can generally be classified into two major groups: classical and intelligent. Although classic methods show excellent performance in protection systems, intelligent methods cover unpredicted events and can extend themselves for future considerations. It is worth noting that there are numerous applications that classical methods are used along with intelligent methods for feature extraction with high recognition rate. The most common classical methods used to identify electrical faults are methods based on frequency analysis such as short time Fourier transform (STFT) and wavelet-transform [2-5]. In [5], the fault is detected in induction motor using wavelet transforms and filter bank with a narrow width. Note, however that these approaches have high computational cost [6] and certain limitations such as impossible analysis of combined signals, they cause reduce speed and accuracy of protection system. These methods are also used to identify the fault in synchronous machines especially permanent magnet synchronous motor (PMSM) [7-9]. In papers [10] and [11], one of the conventional analytical approaches named Motor Current Signature Analysis (MCSA) has been used to detect inter-turn fault in the PMSM Motor. Note that this method signal processing is done on the motor current using different methods and necessary information is extracted. But it is important that the accuracy of this method depends on several factors including: vehicle speed should be fixed and known; it must be measured precisely in induction Slip machines, and load should be preferably fixed [11].

As we noted previously, due to the weaknesses of the classical methods, specialists' willingness has increased to use the heuristic and intelligent methods. Different types of neural networks are one of these intelligent methods [12-15]. In [16] neural network is used to isolate the input current from internal faults. It is valuable to mention that this article has used common neural network to compare suggested method with RBF one that used the Principle Component Analysis (PCA) to extract data required for training network.

It is noteworthy that in this study in addition to fault identification, quantitative evaluation of faults in winding is another issue that is more important to us. For example, we want to know how percentage of a stator winding of PMSM motor is damaged and how its percentage is healthy, and how long the motor can continue to work in this situation (fault conditions). At first, it may seem unnecessary, but when this type of motor is used in critical applications, its importance increases. One of the articles in this issue is the paper [17]. In this paper, Adaptive Neuro-Fuzzy inference system known to summarize ANFIS has been used in order to determine the winding fault percentage of a synchronous generator. As noted in this paper, stator winding fault in synchronous generator seems to be very serious, because winding fails relate to currents higher than the fault and cost of maintaining directly. If this type of fault doesn't remove properly, it may cause irreparable damage. The question that arises here is that which one leads to lower cost: design of an intelligent system for qualitative and quantitative evaluation of Inter-turn stator winding fault, replacement of the motor winding or replacement of the generator?

In this paper, permanent magnet synchronous motor is simulated under fault conditions in the SIMULINK, using SIMPOWER elements. When data required to train the system in different condition has been extracted, minimum distance classifier (so-called 1-NN classifier) is used as a tool to identify Inter-turn stator winding fault. The system is also designed in such way that if occurred fault is an Inter-turn stator winding one, system immediately will be placed in circuit and finds out the fault percentage. This system is based on neural network trained by intelligent optimization algorithms.

In the rest of this paper, improved version of Gravitational Search Algorithm which is one of the contributions of this paper is presented in section 2. Section 3 shows the proposed training method for ANN. Simulation and discussion on obtained results are presented in section 4. And finally conclusion is presented in section 5.

2. Improved Gravitational Search Algorithm (IGSA)

One of the main issues that has attracted the experts, researchers and engineers is finding an efficient and robust algorithm to solve the optimization problems. Gravitational search algorithm (GSA) is a population-based heuristic search algorithm that has been proposed in 2009 by Mrs. Rashedi. This algorithm uses gravity rules and concepts. In this algorithm, each particle will attract other particles due to gravity. At GSA agents are considered as objects and their performances are defined by their mass and computed using the fitness function. Position of any object (agent) corresponds to the solutions of problem. All objects are attracted to each other by gravity and the heavier mass has higher absorption amount than the rest of the objects as shown in Figure 1 (a) which means it can attract other masses. Due to the forces of the other elements (objects) imposed on an agent; this object feels the space around itself, and gravity force acts as a means of information transferring. Thus, heavier objects are effective elements and move more slowly than lighter objects. This condition rescues algorithm to be trapped in a local optimum in search duration for the optimal solution [18].

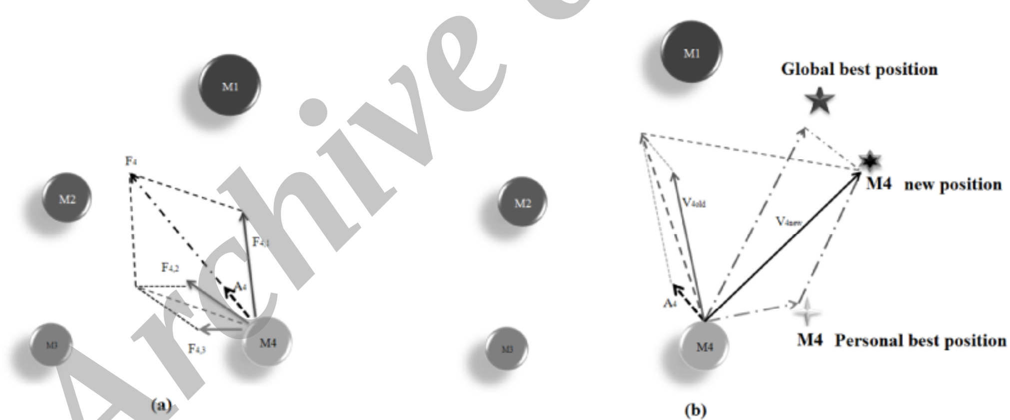


Figure 1. movement of against (a) in GSA, (b) in IGSA

Since the gravitational search algorithm has no memory, some applications are not affected and cannot reach to optimal solution. It seems that adding a memory to this algorithm solves this problem. In this study it has been done by inspiring of PSO algorithm. Like PSO algorithm, a P_{best} indicates the best answer obtained by each agent and a G_{best} indicates the best answers achieved by all parameters so far, these values are defined for GSA and increase its velocity as shown in Eq. (1). Equation (2) shows the movements of agents in solution space.

$$v_i^d(t+1) = rand \times v_i^d(t) + a_i^d(t+1) + rand \times C_1 \times (x(t) - x_{pbest}) + rand \times C_2 \times (x(t) - x_{gbest}) \quad (1)$$

$$x_i^d(t+1) = v_i^d(t+1) + x_i^d(t) \tag{2}$$

As it shown in Figure 1, adding this type of memory allows agents in the GSA to exchange information among each other in every repetition and also become aware of the best situation from the start of the search until now and the best obtained answer, so they can remain in better condition.

3. Neural network training using improved gravitational search algorithm

The human brain is one of the greatest wonders of creation. This wonderful creation is able to process information fast with high efficiency by neural networks composed of large number of neurons. The human brain has the ability to be aware of his surroundings and performance that named the memory. Neural networks are very complex, nonlinear systems with a high degree of freedom that use different topologies to process information. So, in the last half century, the scientists have done many efforts to promote theory of different neural networks. Consequently, the result of all efforts in the past and present years leads to develop artificial neural networks that are mathematical models of real neural networks.

Various methods have been proposed for training the neural networks that are iterative based and use the first and second derivatives in the calculations. Several questions arise, are such methods the best training methods? Are there ways to reduce the computational cost? And questions like these that highlight the problems in these methods. If we look at the problem of training neural networks well, we can consider them as optimization applications. What is the aim of training the neural network (however, we discuss in this section the education with monitoring)? The goal is to update the network weights, so that the neural network output is similar to the target output or in other words our desired output or optimal output. In order to provide a better means, let's examine a simple example. Figure 2 shows a simple perceptron.

Eq. (3) is mathematical model of the network shown in Figure 2.

$$f = g[(\sum_{i=1}^{n} w_i x_i) + b] \tag{3}$$

Where w_i is network weights, x_i, input network, b, applied bias and g activity function that has been described previously. According to Eq. (3), x_i is constant, g is also a function, and w_i and b are variables, therefore, it can be said that changes of output value are related to changes of w_i and b, it means that output of the artificial neural network can be a function of the weights and biases.

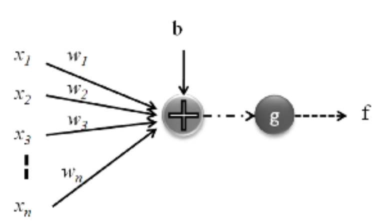


Figure 2. A simple structure of percepteron

$$f = y(w_i, b) \tag{4}$$

We assume that the optimal point of f (.) Function is the target output, so the set of different answers can be considered for w_i and b, the best solution between them calculate optimal value of f (.) function. As we have seen, a neural network training problem is an optimization problem and it can be addressed by using mentioned optimization algorithms (training ANN). As shown in Figure 3, training neural network optimization algorithm can be divided into several parts.

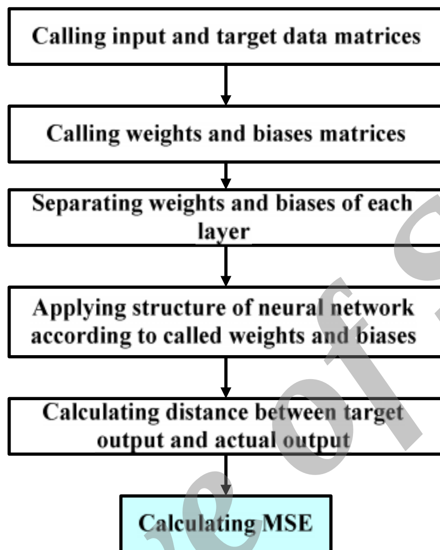


Figure 3. The flowchart of what happens in fitness function when is called

First Phase) to determine initial parameters:

At this stage, the artificial neural network structure, initial parameters and control parameters of population-based algorithms used for incipient planning are set. The number of layers and neurons in each layer must be determined to identify the structure of artificial neural network. To create this neural network, feed forward topology is used; this topology doesn't need any classical training and this kind of network called the multi-layer feed forward neural network. After determining the structure of the neural network, used algorithm parameters should be adjusted, but dimensions of problem are the same for all the algorithms, or in other words the dimensions of answers that depend on number of synaptic weights and biases in neural network. Calculating the number of weights and MLFFNN biases is expressed by an example, suppose we have a MLFFNN that has two hidden layers and one output layer. The number of neurons in layers I, II and III are considered θ, β, and γ respectively, then the number of weights and biases is calculated using the Eq. (5).

$$W = [(\text{the number of Input Data}) \times \theta + b_1] + [\theta \times \beta + b_2] + [\beta \times \gamma + b_3] \tag{5}$$

And finally, the initial position of the particles (agents) in the solution space should be chosen randomly and each of them has a W dimensions.

Second Phase) Applying the population-based algorithm
In this stage, population-based algorithm is used to train the MLFFNN neural network. First, fitness function can be MSE which is called, however, what happens in this function is not a simple relationship but it is complete process as shown in flowchart (3):
As can be seen, first, the matrix of input data and target output is called. Then, the weights and bias matrices will be called that is shown in Eq. (6) as an example.

$$w_i = [p_1, p_2, ..., p_\theta, .p_{\theta+1}, .., p_{\theta+1+b_1\theta}, ..., p_n] \tag{6}$$

Here, w_i is the position of i^{th} in the solution space. In other words, the vector of Eq. (6) reflects the values of weights and biases of MLFFNN network. Then, w_i matrix must be broken to sub matrices to form the neural network structure. Sub-matrices show the weights of a layer and its biases, for example, P_1 to P_θ related to the synaptic weights between input and hidden layers and $P_{\theta+1}$ to $p_{\theta+1+b_1\theta}$ related to biases of the first layer. Network structure can be formed after separation of the sub matrices that can be seen in the Eqs. (7) to (12).

$$S_1 = W_\theta \times [ID] + b_1 \tag{7}$$

$$S_2 = \log sig(S_1) \tag{8}$$

$$Z_1 = W_\beta \times [S_2] + b_2 \tag{9}$$

$$Z_2 = \log sig(Z_1) \tag{10}$$

$$O_1 = W_\gamma \times [Z_2] + b_3 \tag{11}$$

$$O_2 = \log sig(O_1) \tag{12}$$

In the above equations, ID is input data matrix. W_θ, W_β and W_γ are weights between the input, weights between the first layer and second layer and weights between the second and third (or the output layer) layers, respectively. b_1, b_2 and b_3 are biases of first, second and third layers, respectively. For example, sigmoid activity function is used. Finally, value of MSE function is the difference between actual output which here is O_2 and target output. Eq. (14) shows how to calculate this amount.

$$MSE = \frac{\sum_{M,N} (O_2 - TO)^2}{M \times N} \tag{13}$$

Here TO is target output, M and N are the dimensions of the O2 and TO matrices.

The third stage) update agents' information
After assessment of possible answers, the algorithm parameters such as speed, position, etc., should be updated to obtain efficient solutions in the following stages.

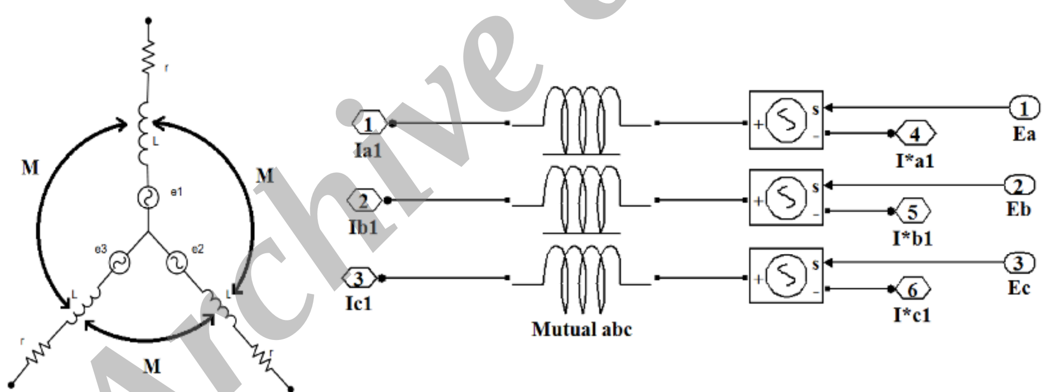
Fourth Stage) stopping criteria
As we know, for all the iterative based algorithms, the stopping criteria are considered, these criteria may be zero or the minimum value of MSE or algorithm iterations.

4. Simulation and results

In order to demonstrate the ability of the proposed approach presented in this paper, these methods were tested under different conditions. But first it is necessary to simulate PMSM model under normal and fault conditions. After the PMSM has been designed by considering the parameters and ensuring the accuracy of the simulations in MATLAB/SIMULINK, waveform or in other words, necessary information is extracted from the motor. Since presented methods are intelligent, we require training data obtained by sampling. It means that Inter-turn stator winding fault with different fault percentages is simulated under controlled conditions and training data are selected randomly. After training, the proposed methods are used in simulation as intelligent detective system to detect Inter-turn stator winding fault and calculate the amount of these faults intelligently.

4.1.Simulation of PMSM under Inter-turn stator winding fault

The elements found in the SIMPOWER system library were used in order to provide more accurate and realistic simulation in this study. As shown in Figure 4 (b), a three-phase mutual inductance considering model of Figure 4 (a) completely, is used to model a PMSM under normal conditions.



(a) Equivalent circuit of PMSM under healthy conditions

(b) Mutual inductance element in SIMPOWER system library used to model PMSM under healthy condition

Figure 4. Simulation of PMSM under healthy condition

Figure 5 shows overview of the PMSM simulation (Drive Control System) that is identical in all circumstances, whether in normal conditions or under faults conditions. As can be seen in Figure 5 after the transformation of the three phases current of the abc domain to the dq domain, these obtained currents are used to compare in the entrance, and finally the motor is set up and controlled by obtaining the V_d and V_q voltages and their application in PWM.

4.1.1. Equivalent circuit of the motor under fault conditions.

As already mentioned, the more accurate and efficient model can result the better fault identification and the more accurate designing of fault diagnosis system. Electrical faults are the most common faults that may occur in stator winding of PMSMs. Usually windings faults relate to insulation defects. But experts believe that the origin of the electrical faults that often occur in the stator winding is Inter-turn stator winding fault occurring in every turn of winding that grows and eventually leads to these faults [19]. So, importance of inter-turn stator winding fault identification in every turn of winding becomes more obvious. It is worth noting that the winding insulation may be impaired due to several reasons, some of them are mentioned as follow: 1- High temperature of winding or core of stator; 2- Lamination slack, slot wedge and connections; 3- Disappearance of the end pins of the winding; 4- Oil, humidity and dirty pollution; 5- Short circuit and starting the pressure; 6- Electrical load discharge; 7- Leaking in the cooling system. In this paper, we try to model some electric faults in stator winding. Then we will model Inter-turn stator winding fault, Inter-turn stator between two phases (two windings) of stator and lamination winding fault (opening the circuit) of one of the stator phases.

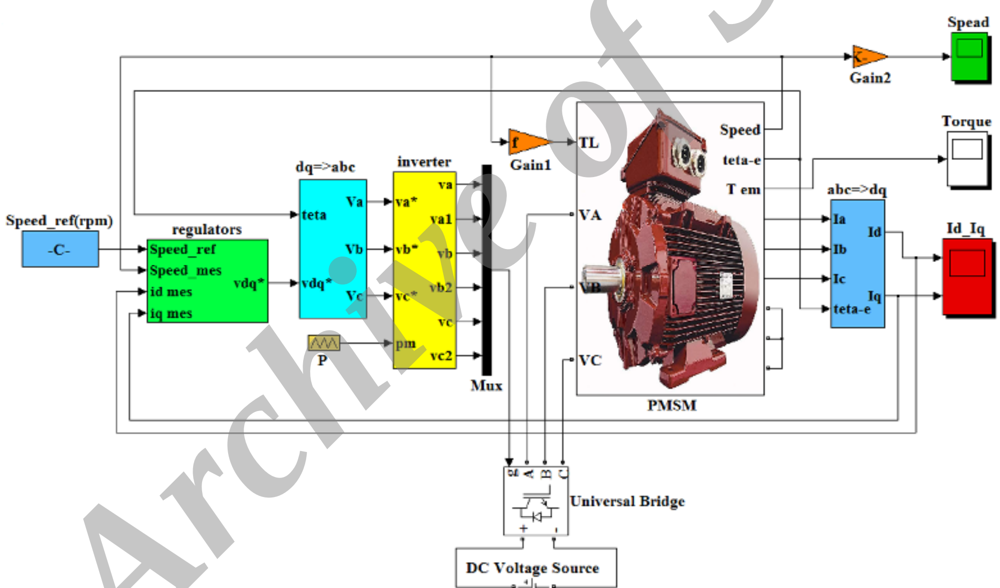
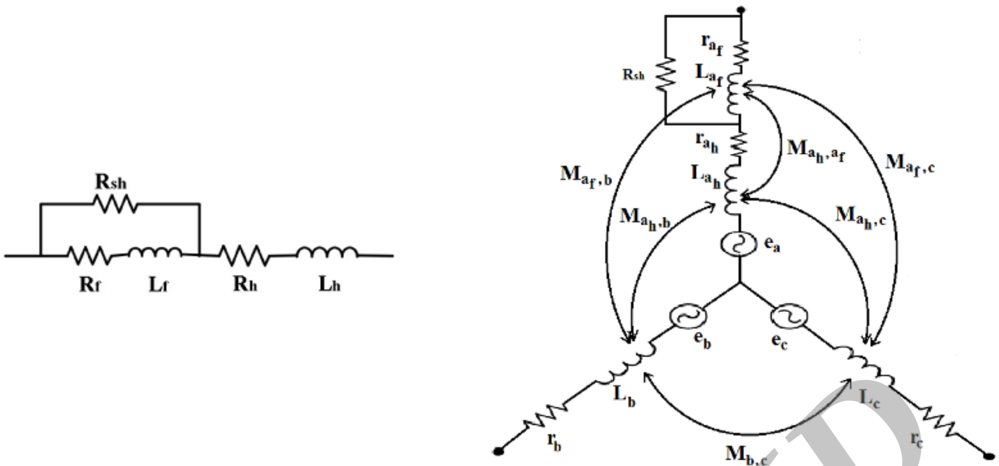


Figure 5. Block diagram of the closed loop drive system for PMSM simulated motor under healthy condition* (normal) in MATLAB/SIMULINK *software.

4.1.2. Designing PMSM under Inter-turn stator winding fault

As noted above, this type of fault is the most common fault that may occur in an electric machine, especially the PMSM. This type of fault can be shown by a short circuit resistance in the simplest case as Figure 6 (a). However, when such a fault occurs in a PMSM, issue is more complex than a simple model (see Figure 6 (b)).



(a) A simple model of Inter-turn stator winding fault

(b) Circuit model of PMSM under inter turn fault in winding of phase "*a*"

Figure 6. Equivalent Circuit of PMSM under inter-turn fault considering mutual inductance between healthy and damaged parts in faulted phase

Mutual induction between stator windings is identical in the normal mode, and inductance and resistance modeled in the winding are similar and have the same values for other windings. But when an Inter-turn stator winding fault (turn to turn) occurs in stator winding, its resistance and inductance vary and subsequently passing flux and current in that winding vary. However since the turn to turn fault in incipient steps is not considered as complete Inter-turn stator winding fault and also presence of carbon and other materials results resistance in defective parts, defective winding is divided to two parts: healthy and damaged ones, every part has mutual induction with other phases separately, in the other hand, between these two parts may be mutual induction; this issue is considered in simulation of winding fault. Figure 6 shows a circuit model of PMSM under the condition of inter-turn stator winding fault in phase a of stator winding, that all above mentioned considerations are considered in it.

In fact, if we assume that N_f be the number of turns (rings) of winding with Inter-turn stator winding fault, then percentage of winding fault (X_f) is calculated by Eq.(15).

$$N_h = N - N_f \tag{14}$$

$$X_f = \frac{N_f}{N} \tag{15}$$

Where N is the total number of turns (rings) in the winding and it is the same in all phases. N_h is the number of healthy turns of defective winding. . In the other hand, we know that resistance and inductance of a winding relates to the number of its turns:

$$\begin{cases} R \;\alpha\; N \quad \Rightarrow \mathrm{R} = \rho \dfrac{\mathrm{l}}{\mathrm{A}} \\ \mathrm{L} \;\alpha\; \dfrac{\mathrm{N}^2}{\mathrm{R_m}} \Rightarrow L = \dfrac{N^2}{R_m} \end{cases} \tag{16}$$

Nomenclature *A* is the cross section of the winding, ρ specific resistance of the winding, l is the length of the winding and R_m is resistance of magnetic current. According to the above equation, the values of resistance, inductance and mutual inductance for a defective phase are calculated by Eqs. (17) to (24). It follows that the relationship between "a_h" indicates healthy part of defective winding and "a_f" indicates damaged part of defective winding. r_a and *La* are winding resistance and winding inductance, respectively.

$$r_{a_f} = \frac{N_f}{N} r_a = X_f \ . \mathrm{r_a} \tag{17}$$

$$r_{a_h} = \frac{N - N_f}{N} r_a = (1 - X_f) \ . \mathrm{r_a} \tag{18}$$

$$\frac{L_{a_f}}{L_a} = \frac{\dfrac{N_f^2}{R_m}}{\dfrac{N^2}{R_m}} = \frac{N_f^2}{N^2} = X_f^2 \Rightarrow L_{a_f} = X_f^2 \ . \mathrm{L_a} \tag{19}$$

$$\frac{L_{a_h}}{L_a} = \frac{\dfrac{(N - N_f)^2}{R_m}}{\dfrac{N^2}{R_m}} = \frac{(N - N_f)^2}{N^2} = (1 - X_f)^2 \Rightarrow L_{a_h} = (1 - X_f)^2 \ . \mathrm{L_a} \tag{20}$$

If the mutual induction between two windings is calculated by the Eq. (21), then we have the Eqs. (22) and (23):

$$M = \frac{N_a N_b}{R_m} = \frac{N^2}{R_m} \tag{21}$$

$$M_{a_f,b} = \frac{N_{a_f} N_b}{R_m} = \frac{X_f NN}{R_m} = \frac{X_f N^2}{R_m} = X_f \ . \mathrm{M} \tag{22}$$

$$M_{a_h,b} = \frac{N_{a_h} N_b}{R_m} = \frac{(1-X_f)NN}{R_m} = \frac{(1-X_f)N^2}{R_m} = (1-X_f)\ .\ \mathrm{M} \tag{23}$$

In above equations r_{a_f} and r_{a_h} are resistance of defective winding for the damaged and normal parts of phase a respectively, L_{a_f} and L_{a_h} defective winding inductance of the damaged and normal parts of phase a respectively. M is the mutual induction between two healthy windings, $M_{a_f,b}$ is mutual induction between the damaged part of winging and a total b phase of winding, and $M_{a_h,b}$ is mutual induction between healthy part of phase a of winding and total winding of the phase b. As mentioned before, the change of flux in healthy and burned portions of the winding of a phase can result mutual induction, between them phase a between them, considering this change and resulted induction increases the accuracy of simulation, and it is calculated by Eq. (24).

$$M_{a_f,a_h} = \frac{N_{a_f} N_{a_h}}{R_m} = \frac{[X_f\ .\ \mathrm{N}].[(1-X_f)N]}{R_m} = X_f(1-X_f)\frac{N^2}{R_m} = X_f(1-X_f)\ .\ \mathrm{L_a} \tag{24}$$

It is worth noting that $\frac{N^2}{R_m}$ here is inductance of phase "*a*" but not mutual interaction between two windings. Writing KVL in three turns of circuit in Figure 6, the windings voltages are:

$$V_a = X_f e_a + r_{a_f} i_{a_f} + L_{a_f}\frac{di_{a_f}}{dt} + M_{a_f,b}\frac{di_b}{dt} + M_{a_f,c}\frac{di_c}{dt} + M_{a_f,a_h}\frac{di_{a_h}}{dt} + \dots$$
$$\dots. + M_{a_h,a_f}\frac{di_{a_f}}{dt} + (1-X_f)e_a + r_{a_h} i_{a_h} + M_{a_h,b}\frac{di_b}{dt} + M_{a_h,c}\frac{di_c}{dt} + L_{a_h}\frac{di_{a_h}}{dt} \tag{25}$$

$$V_b = e_b + r_b i_b + L_b\frac{di_b}{dt} + M_{b,a_f}\frac{di_{a_f}}{dt} + M_{b,a_h}\frac{di_{a_h}}{dt} + M_{b,c}\frac{di_c}{dt} \tag{26}$$

$$V_c = e_c + r_c i_c + L_c\frac{di_c}{dt} + M_{c,a_f}\frac{di_{a_f}}{dt} + M_{c,a_h}\frac{di_{a_h}}{dt} + M_{c,b}\frac{di_b}{dt} \tag{27}$$

In the above equations $M_{a_h,a_f} = M_{a_f,a_h}$, $M_{b,a_f} = M_{a_f,b}$, $M_{b,a_h} = M_{a_h,b}$, $M_{c,a_h} = M_{a_h,c}$, $M_{c,a_f} = M_{a_f,c}$ and $M_{c,b} = M_{b,c}$. Considering these relationships, model of PMSM is simulated under fault winding conditions using Eqs. (17) to (24) and (25) to (27) in SIMPOWER system of MATLAB software. Then, block of the PMSM machine (motor) simulation under fault conditions is achieved by placing the defective model instant of the normal model in Figure 5.

4.2.Results and discussion

Since both fault detection and fault amount be considered, obtained results for each examination fall in two parts. Also, in order to compare with the results of proposed method, results of other methods are presented. Methods based on neural network, such as Feed-Forward Back Propagation Neural Network, Cascade Back Propagation Neural Network and Radial Basis Neural Network, are used in order to show the ability of the minimum distance classifier (1-NN) [20] to detect faults. Remarkably, the best structure for the networks is considered by trial and error training. MSE value is used as a criterion of training performance for all methods based on neural network. Also three hidden layers with (6-12-18) neurons are used to design and train FFBPNN and CFBPNN neural networks. According to conducted experiments mentioned number of layers and neurons have been presented the best results, in addition, according to analysis the best recognition rate on training data obtained by activity function of *tansig* in middle (hidden) and activity function of *Purelin* in output layer. Furthermore, as mentioned a method based on neural network trained by improved gravitational search algorithm is used to determine the percent fault, also other algorithms based on swarm intelligence such as basic *Particle Swarm Optimization* (PSO) and basic *gravitational search algorithm* (GSA) are used to compare the results, and the results obtained from Feed-Forward Back Propagation Neural Network, Cascade Back Propagation Neural Network and Radial Basis Neural Network are presented in order to prove the ability of this training method.

It should be noted that the selecting the appropriate models for the study as well as the designing the intelligent and efficient system is important. Extraction of appropriate patterns and signals from the motor under different operating conditions can provide the useful information for designer. Therefore, as it can be seen in Figure 7, the per unit values of three-phase currents is used to detect the faults and also, per unit magnitude of the negative alternating currents [21] is used as a model to determine the amount of the fault.

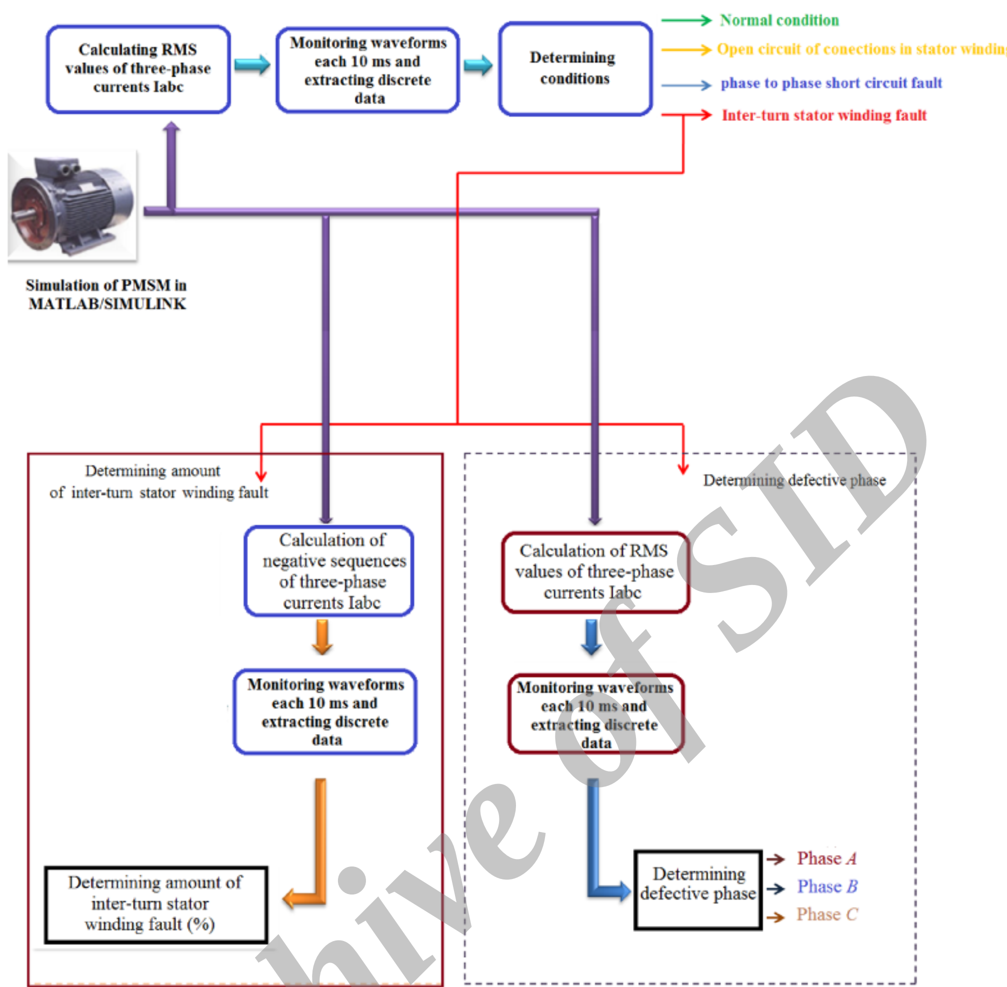


Figure 7. total performances of proposed intelligent protection system

In following, some situations will be discussed, as instants, to test the proposed system. Although there are more possible cases of evaluation and testing, the two conditions are satisfied: the condition that its fault percentage is less than 10% and the one that its percentage fault is high for example more than 80%. Table (1) shows the details of the studied PMSM and Table (2) shows information of case studies. It is necessary to mention that the Inter-turn resistance for simulation of PMSM equals 0.05 ohms under Inter-turn stator winding fault condition, and different amount faults in different phases are extracted, in addition, Inter-turn resistance in the range of 0.01 to 7 ohms is used to extract the data from simulated PMSM under Inter-turn stator winding fault condition between two windings.

Table 1. Studied PMSM parameters

Parameters	Values
Source voltage	560 V
Inductance of each healthy winding (L)	1.182 (mH)
Mutual Inductance between two healthy winding (M)	0.136 (mH)
Resistance of each healthy winding (r)	0.016 (Ω)
Moment of inertia (J)	0.1 (kg.m2)
Friction factor (f)	0.01
Rated speed	2500 (rpm)

Table 2. Case study problems for evaluating designed system

Case study	condition
First condition	9 percent inter-turn stator winding fault in phase a
Second condition	83 percent inter-turn stator winding fault in phase c

4.2.1. The first condition (Inter-turn stator winding fault in phase a with amount of 9%)

Proposed methods must have optimal performance in all fault conditions. An intelligent system should identify the fault type and its state in the least possible time in all tested cases. The first condition is one of the primary cases of Inter-turn stator winding fault; this kind of fault, in actual condition, can be identified hardly. As it can be seen in Figure 8 (a) and (b) there is not a significant change in motor speed and RMS per unit values of the three-phase stator currents. Magnitude of negative sequence components of three-phase currents is used in order to determine the fault amount of Inter-turn stator winding fault. Therefore, Figure 8 (c) shows per unit magnitude of negative sequence components of three-phase stator currents under these conditions. Figure 9 shows the performance of the proposed method in such circumstances to detect inter-turn fault. For the studied case, intelligent systems must identify "2" situation. Figures 10 shows performance of designed intelligent system contained trained neural networks to determine the fault amount in comparison with standard neural networks under mentioned fault conditions.

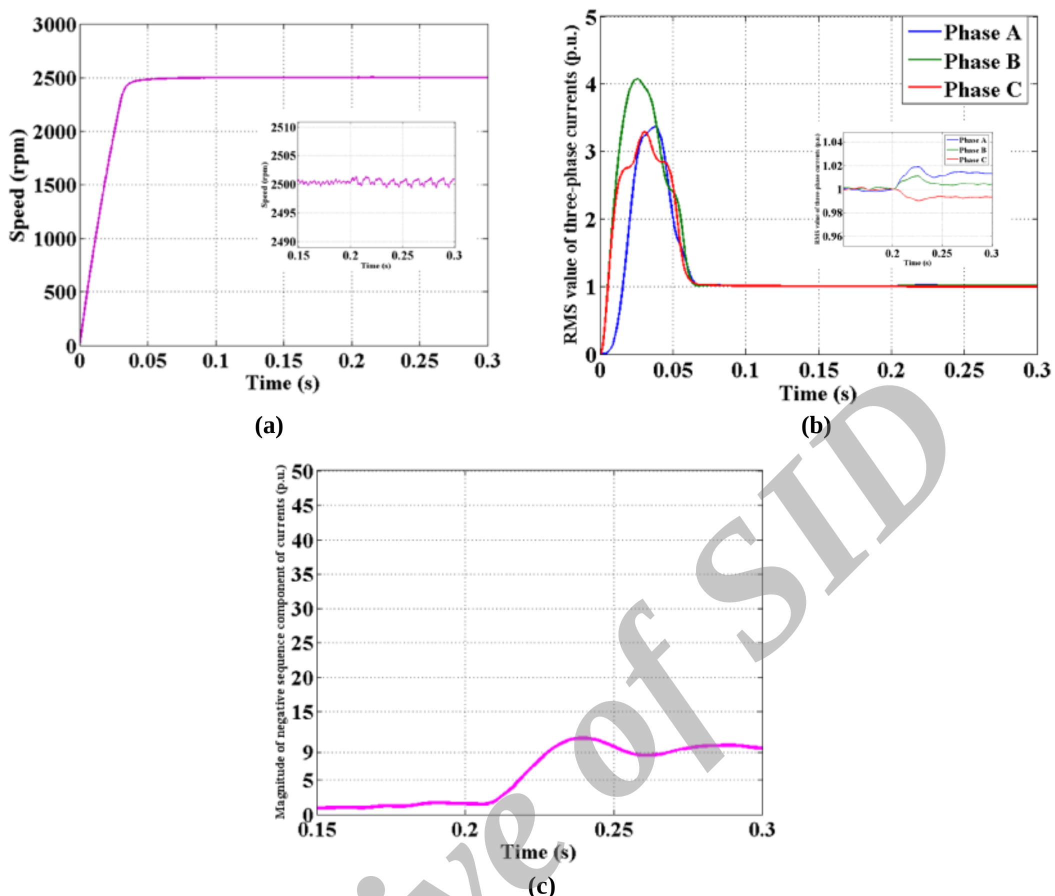
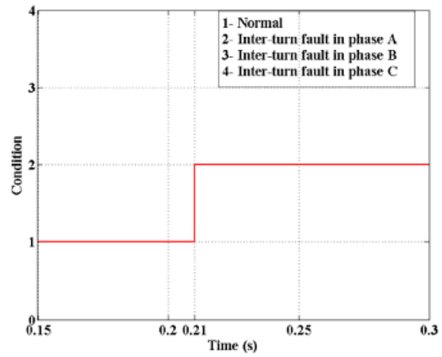
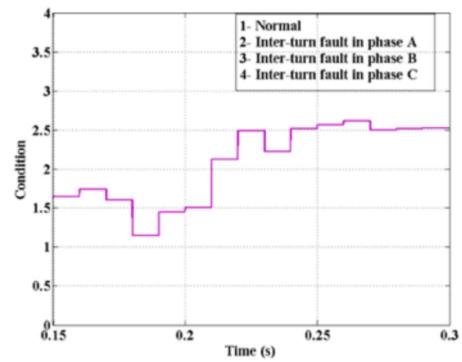


Figure 8. PMSM under 9 percent of Inter-turn stator winding fault in phase a and in the time of 0.2 sec. (a) motor speed, (b) RMS values of Per-unit currents of three phases, a, b, and c, in the stator, (c) Magnitude of per unit value of negative sequence components of three-phase currents

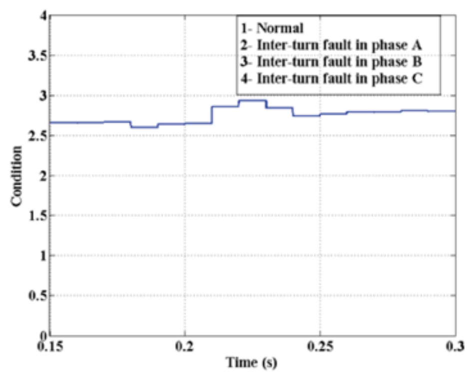
As it can be seen in Figures 9 (a) although the amount of fault is low and we have a light fault here, the proposed method detects inter-turn fault and faulty phase less than half duty cycle about 10 millisecond and then follow amount of happened fault about a duty cycle. This delay can be caused by our sampling method which monitors a waveform each 10 millisecond. According to the performance of other methods, it can be implied that none of the traditional ANN topologies can follow fault condition. In addition, from obtained results the best performance to predict amount of fault is for ANN trained by IGSA. Although FFBPNN has the same performance, it will be illustrated that FFBPNN shows good performance only for light faults while it presents bad performance in heavy inter-turn faults (see Figure 10 from (a) to (f)).



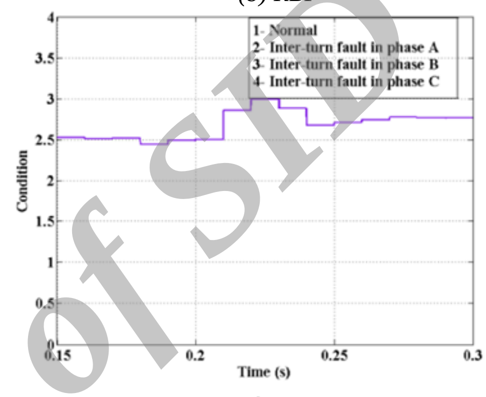
(a) *Minimum distance classifier (1-NN classifier)*



(b) RBF



(c) FFBPNN

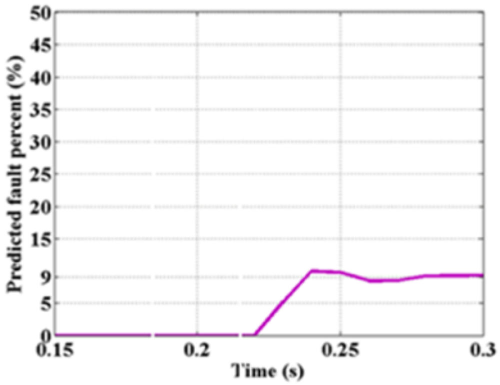


(d) *CFBPNN*

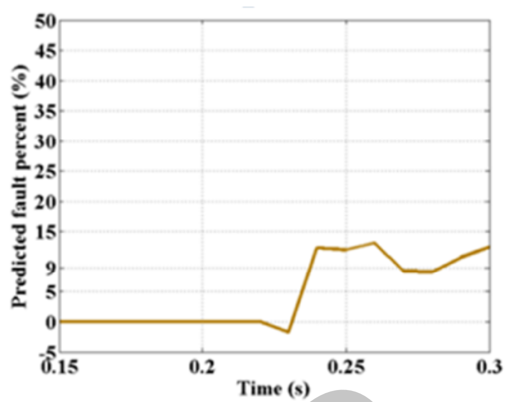
Figure 9. Performance of minimum distance classifier in comparison with other ANN-based methods in detection of 9 percent of Inter-turn stator winding fault in phase a

4.2.2. The second condition (Inter-turn stator winding fault in phase c with fault amount 83%)

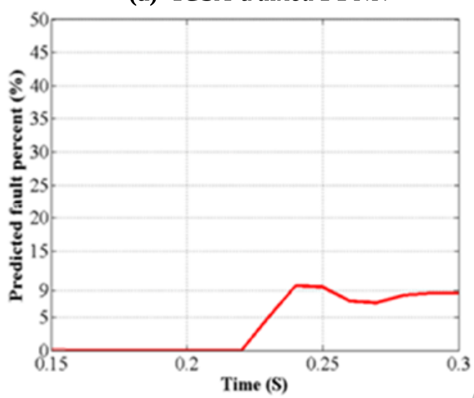
As it is difficult to determine the fault amount in low fault rates (such as first condition), it also seems very difficult to determine the fault amount in high fault rates, because motor performance in low percentages fault is similar to normal mode, and the changes of motor parameters are minimal in high percentages fault, especially more than approximately 70% and 80%. So it would be a negative impact on system performance. As Figures 11 (a) and (b) show, this fault amount may create highly significant changes on the waveform of three-phase currents and their RMS per unit values.



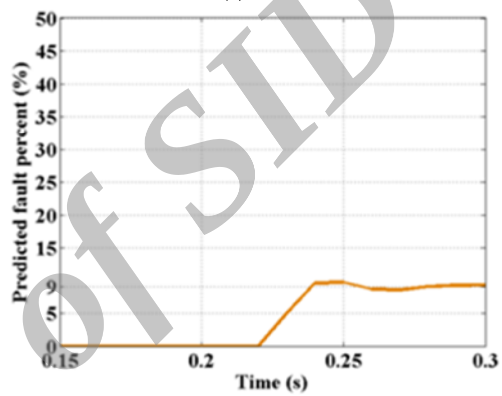
(a) ***IGSA-trained FFNN***



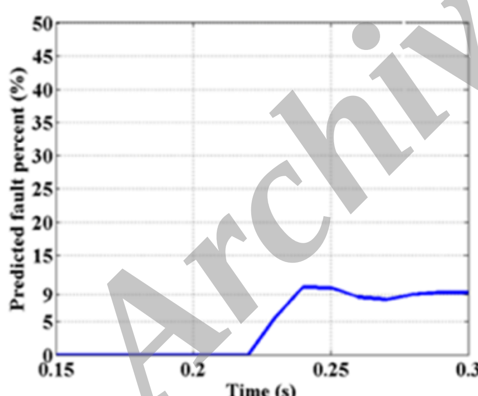
(e) RBF



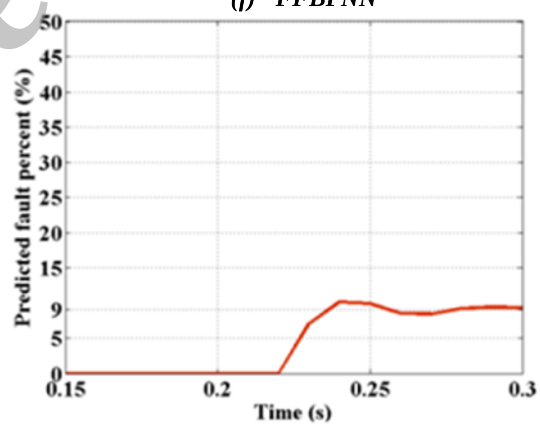
(b) ***GSA-trained FFNN***



(f) FFBPNN



(c) ***PSO-trained FFNN***



(g) ***CFBPNN***

Figure 10. Performance of designed intelligent system based on trained feed forward neural network (FFNN) using IGSA to follow 9 percent Inter-turn stator winding fault in phase "a" in comparison with GSA and PSO trained FFNN and other ANN-based methods.

The Figure 11 (c) shows per unit magnitude of negative sequence components of three-phase stator currents under fault amount 83% in c phase. Noted that intelligent fault detection systems must register "4" situation when the system works normally. Figures 12 (a-d) show performance of used method under these conditions. In this case that Inter-turn stator winding fault is very severe, as shown in Figure 13, the proposed method works well in this situation. On the other hand, apart from inability of RBF and

CFBPNN neural networks to identify the normal condition, these two networks approximately can record “4” situation after about three cycles (60 milliseconds) as shown in Figure 13.

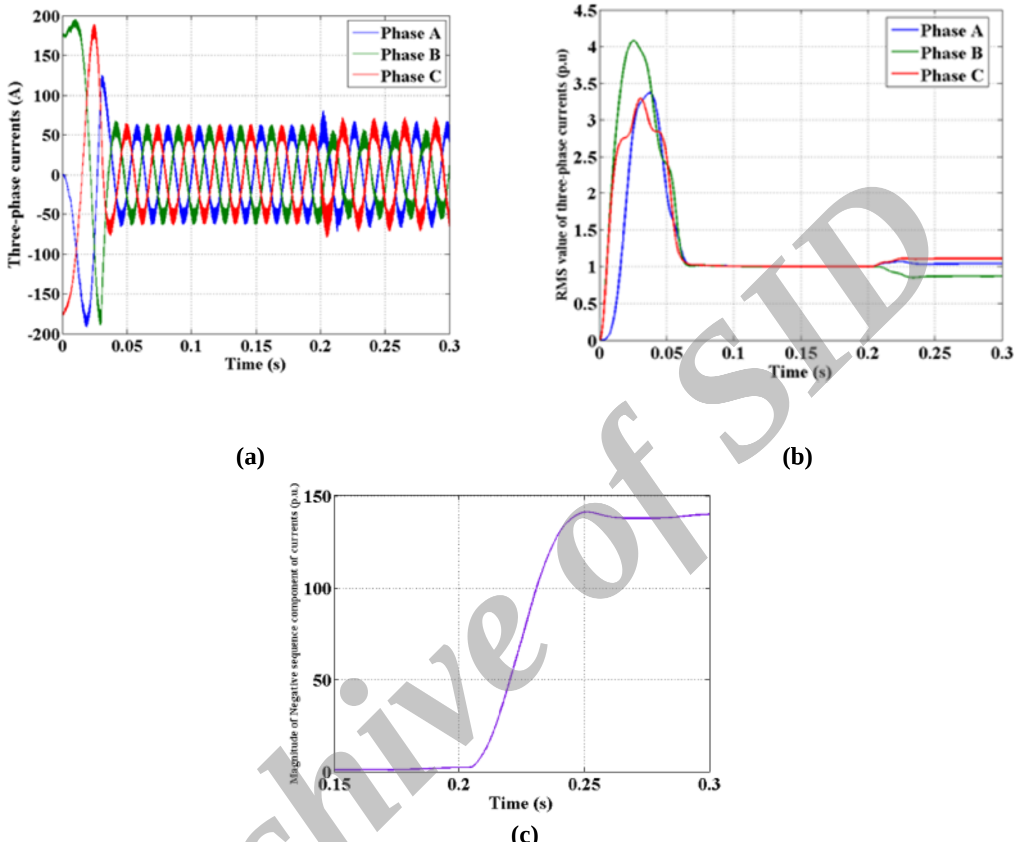
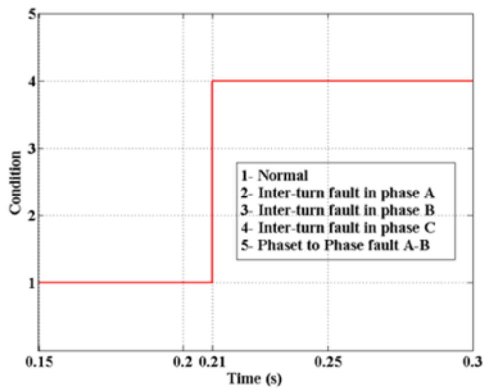
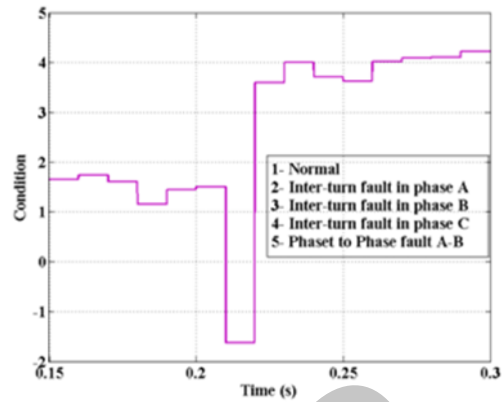


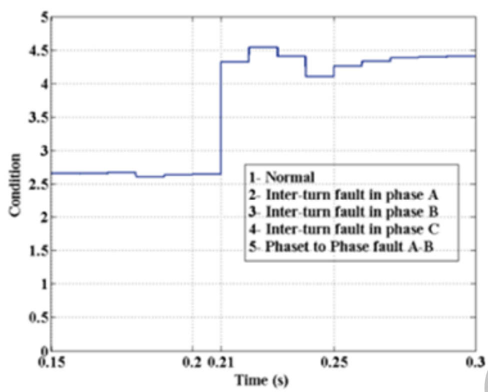
Figure 11. PMSM under 83 percent of Inter-turn stator winding fault in phase a and in the time of 0.2 sec. (a) currents of three phases, a, b, and c, in the stator (b) RMS values of Per unit currents of three phases, a, b, and c, in the stator., (c) Magnitude of per unit value of negative sequence components of three-phase currents



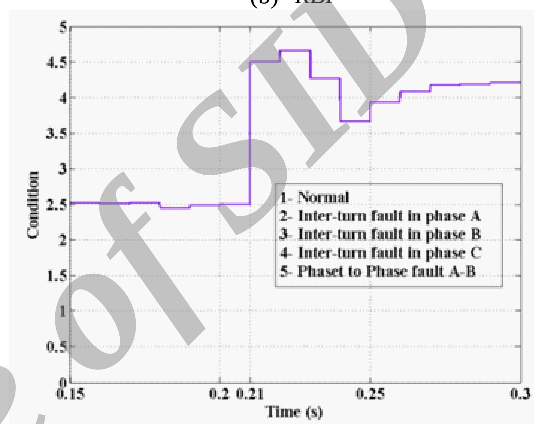
(a) *Minimum distance classifier (1-NN classifier)*



(b) *RBF*

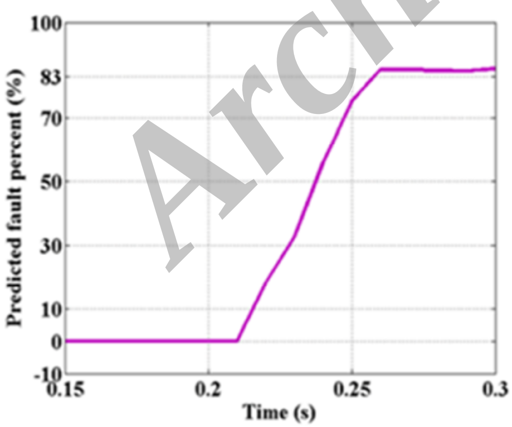


(c) *FFBPNN*

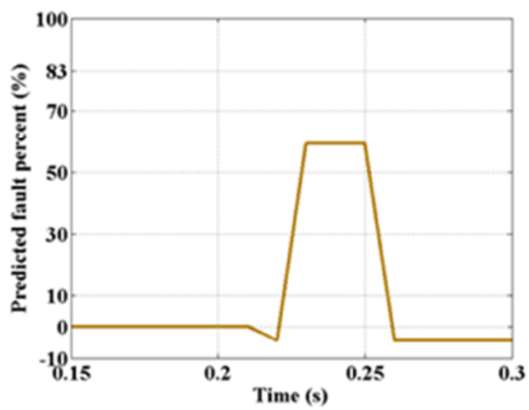


(d) *CFBPNN*

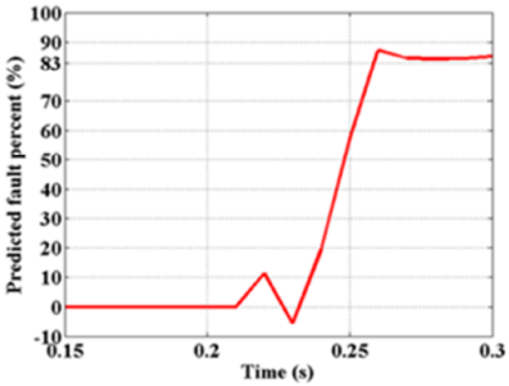
Figure 12. performance of minimum distance classifier in comparison with other ANN-based methods in detection of 83 percent of Inter-turn stator winding fault in phase a



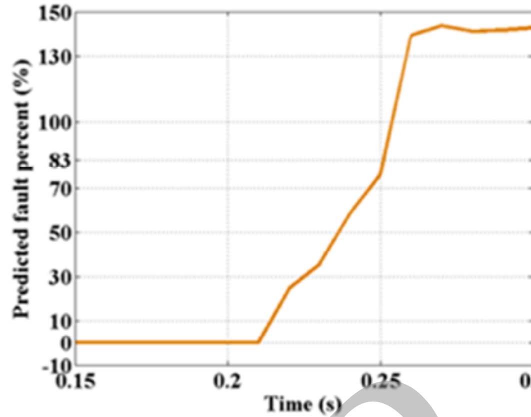
(a) ***IGSA-trained FFNN***



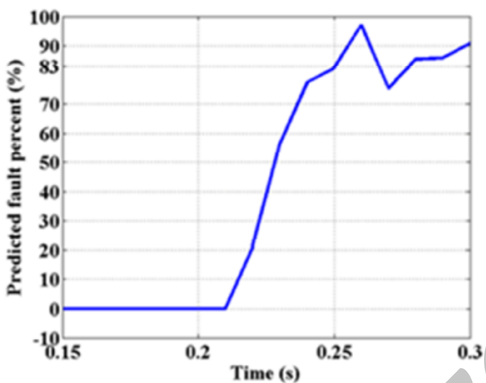
(d) ***RBF***



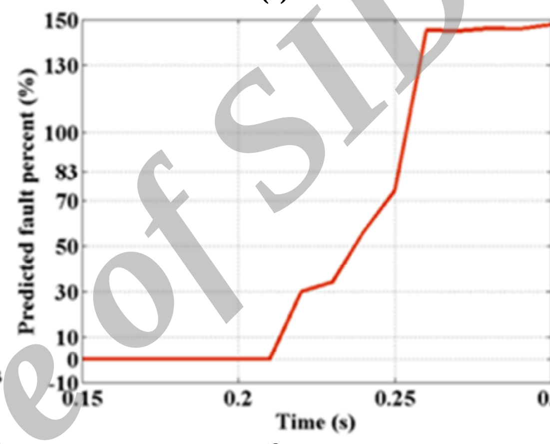
(b) *GSA-trained FFNN*



(e) *FFBPNN*



(c) *PSO-trained FFNN*



(f) *CFBPNN*

Figure 13. Performance of designed intelligent system based on trained feed forward neural network (FFNN) using IGSA to follow 83 percent Inter-turn stator winding fault in phase "a" in comparison with GSA and PSO trained FFNN and other ANN-based methods.

As it can be seen in the results, the proposed method has the best performance in determining the kind of faults as well as recognizing the fault amount. Although some mentioned methods have had good performance, the good performance in every condition is important for a system. For example, in low percentages of fault, the RBF, FFBPNN and CFBPNN have optimal performance to detect faults and determine the extent of damage of winding but their performance grows weaker in high percentage of fault and they cannot detect faults well. In the other hand, according to results, in spite of its simplicity, IGSA algorithm, can optimize the neural network well and provide exact results for intelligent system.

5. Conclusion

Considering specific applications of permanent magnet synchronous motors, it seems imperative to maintain and protect them. As fault is inevitable in systems and equipments, so every permanent magnet synchronous motor may also have mechanical and electrical problems. This research is focused on the electric faults. It is tried to design an intelligent system, firstly, to distinguish the inter-turn stator winding fault from normal mode and two other types of electric faults occurring in winding stator of PMSM, and after detection of inter-turn stator winding fault, to determine fault percent (%). It is valuable to say that SIMULINK and SIMPOWER systems are here used simultaneously. If it be necessary to express obtained results shortly, its expended dimensions must be considered, as in following: In this study PMSM is designed under fault conditions in SIMPOWER system successfully, this system is more accurate than SIMULINK because of its circuit elements. In addition, it has other advantages such as considering change of mutual inductance between phases and even creation of mutual inductance in one phase due to fault occurrence; these advantages lead to high accuracy in simulation. After analysis the different signals (patterns) that may be obtained from motor in fault conditions, efficient per unit values of three- phase stator currents are selected as the best pattern to recognize inter-turn stator winding fault and determine detective phase, because these signals (patterns) can be used to identify fault and detective phase, simultaneously. The signals (patterns) have the capability of being able to help others as well as the fault is detected and the faulty phase is detected. Also pattern of magnitude of negative sequence component of three- phase stator currents is used to determine the fault amount of inter-turn stator winding fault because of pattern's sensitivity. Because, unlike other models, this pattern can be used when fault amount changes and its steady-state changes according to fault amount, however, it should be noted that these changes are nonlinear.

Various methods are evaluated to separate electrical faults in PMSM and detect Inter-turn stator winding fault, the minimum distance classifier, in spite of its simplicity, indicates the best performance. Obtained results show that the minimum distance classifier can identify fault and detective phase simultaneously in less than one working cycle (in 10 millisecond). Also it is proved that neural networks trained by swarm intelligence algorithms work better than common and general algorithms in determining the amount of Inter-turn stator winding fault. It is also worth noting that according to the obtained results, the improved GSA algorithm is the best option for training neural networks in this field.

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