Faults Diagnosis of BLDC Motors Using Artificial Neural Networks

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Abstract. Recently, brushless DC motor (BLDC) has been implemented in many applications, especially critical applications. Due to many reasons, BLDC motor subjects to many types of faults including electrical and mechanical faults, therefore detect and diagnosis faults is very important in order to keep safety to the motor also reduce cost and maintenance. In this paper, an approach has been presented to diagnose the stator winding faults, control circuit switches fault and bearing faults. Artificial Neural Network (ANN) has been applied to diagnose faults at different operation conditions. The simulation result shows the ability of the proposed technique to diagnose faults with high accuracy.

1. Introduction
BLDC motors have a wide popularity in the industrial application. BLDC motor consists of two parts stator with armature windings and rotor with permanent magnets. This motor does not suffer from electric arcing because there is no mechanical commutator and use an electronic switch circuit instead [1,2] and it is suitable for critical applications due to its advantages such as high efficiency, high power factor, and high speed [3]. Also, it has disadvantage represented by high cost, resonance issue, and complex wiring setup due to the involvement of electronic control.

BLDC motors was subjected to electrical and mechanical faults due to many reasons such as exceeding the standard life time, overload or unbalanced load, mechanical, dynamic and thermal stress and electrical stress from fast switching inverter, downtime, and costly repairs [4].

BLDC Motor faults can be categorized as electrical and mechanical. Electrical faults can be divided to the stator winding fault, rotor fault and control switches fault. Mechanical faults can be divided to bearing faults, broken rotor bar and eccentricity faults. In this work, stator winding current and phase voltage have been used as indicator of electrical faults, while vibration signal from bearing part has been used as indicator of mechanical fault.

Condition monitoring and fault diagnosis of the BLDC motor are necessary to optimize maintenance and improve reliability levels. Many development techniques had been used to implement detection and diagnosis faults in electrical motor such as artificial intelligence (AI) [11,12], model-based [7], and hybrid techniques [8]. AI included many techniques such as Fuzzy Logic System (FLS) [9], Neural Network (NN) [10], Genetic Algorithm[11].

At early stages, NN has an active area, so human expertise becomes traditional with the development of NN. In this paper, Feed Forward Neural Networks (FFNN) has been performed to diagnosis fault based on stator current and phase voltage, and vibration signal.

In [12] Adaptive Neuro-fuzzy Inference System (ANFIS) method was used diagnosis of stator winding faults in BLDC motor. Simulink/MATLAB has been used to analysis the dynamic characteristics to validate the performance of the proposed algorithm for varying load and speed conditions. FLS and NN was performed to diagnosis faults in the bearing part in BLDC motor by use vibration signals as fault indicator[13]. In [14] a comparison between current signal and vibration signal as fault indicator, the analysis result show that; when speed operation is low current signal is suffer from high speed, and bearing faults, broken rotor bar and eccentricity faults.

With regard to the structure of this article, after completion of introduction, BLDC motor mathematical model is presented, while section ‘Gathering data ’ presents how gathering data at different cases and different operation condition. This is follow by a description of an innovative fault classification procedure based on neural network (NN) architecture in section ‘NN architecture for fault classification’. In section ‘NN result’ the results of diagnosis fault based on NN has been presented. Finally, conclusions are given in section ‘Conclusion’.

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2. Modelling of BLDC motor

The voltages of the stator windings are represented by the equation (1) [7]:

\[
\begin{bmatrix}
    v_a \\
v_b \\
v_c
\end{bmatrix} =
\begin{bmatrix}
    R_S & 0 & 0 \\
    0 & R_S & 0 \\
    0 & 0 & R_S
\end{bmatrix}
\begin{bmatrix}
    i_a \\
i_b \\
i_c
\end{bmatrix} +
\begin{bmatrix}
    \frac{d\psi_a}{dt} \\
    \frac{d\psi_b}{dt} \\
    \frac{d\psi_c}{dt}
\end{bmatrix}
\]  

(1)

Where: \((v_a, v_b, v_c)\) are the voltages that applied to the motor, \(R_S\) is the resistance of the stator winding, \((i_a, i_b, i_c)\) are represent the currents flowing in the stator windings, \((\frac{d\psi_a}{dt}, \frac{d\psi_b}{dt}, \frac{d\psi_c}{dt})\) are the change rates of magnetic flux in each stator winding. The flux equation is represented by the following equation:

\[
\begin{bmatrix}
    \psi_a \\
    \psi_b \\
    \psi_c
\end{bmatrix} =
\begin{bmatrix}
    L_{aa} & L_{ab} & L_{ac} \\
    L_{ba} & L_{bb} & L_{bc} \\
    L_{ca} & L_{cb} & L_{cc}
\end{bmatrix}
\begin{bmatrix}
    i_a \\
i_b \\
i_c
\end{bmatrix} +
\begin{bmatrix}
    \psi_{am} \\
    \psi_{bm} \\
    \psi_{cm}
\end{bmatrix}
\]  

(2)

Where: \((\psi_a, \psi_b, \psi_c)\) are the total fluxes linking of the stator windings, \((L_{aa}, L_{bb}, L_{cc})\) are the self-inductance of the stator windings, \((L_{ab}, L_{ac}, L_{bc})\) are represent the mutual inductances of the stator windings, \((\psi_{am}, \psi_{bm}, \psi_{cm})\) permanent magnet fluxes linking of the stator windings.

The inductances are defined by following equations:

\[
L_{aa} = L_s + L_M \cos(2\theta_r)
\]  

(3)

\[
L_{bb} = L_s + L_M \cos(2(\theta_r - 2\pi/3))
\]  

(4)

\[
L_{cc} = L_s + L_M \cos(2(\theta_r + 2\pi/3))
\]  

(5)

\[
L_{ab} = L_{ba} = -M_S - L_M \cos(2(\theta_r + \pi/6))
\]  

(6)

\[
L_{bc} = L_{cb} = -M_S - L_M \cos(2(\theta_r + \pi/6 - 2\pi/3))
\]  

(7)

\[
L_{ca} = L_{ac} = -M_S - L_M \cos(2(\theta_r + \pi/6 + 2\pi/3))
\]  

(8)

Where: \((L_s)\) the stator self-inductance per phase (The average self-inductance for each of stator windings), \((L_M)\) the stator inductance fluctuation (the amplitude of fluctuation in the self-inductance and mutual inductance with changing of rotor angle), \((M_S)\) the stator mutual inductance (the average mutual inductance between the stator windings). The electromagnetic torque can be extracted as:

\[
T_e = J \frac{dw_r}{dt} + K_f w_r + T_l
\]  

(9)

Where: \(T_l\) is the load torque, \(K_f\) is the viscous friction constant, \(J\) is the rotor moment of inertia and \(w_r\) is the rotor speed. Motor speed equation is,

\[
\frac{dw_r}{dt} = \frac{Te}{J}
\]  

(10)

Where: \(\theta\) is an electrical position of the rotor flux.

Figure 1. BLDC motor simulation model in MATLAB.
3. Gathering data for healthy condition

Using a Simulink model in Figure 1, the stator current signals in three phase winding have been get as shown in Figure 2, where the motor operates with rated parameters in Table 1.

Table 1. Rated parameters of BLDC motor.

| Parameter      | Value     |
|----------------|-----------|
| Rated power    | 1.44 KW   |
| Rated current  | 6.5 A     |
| DC Voltage     | 120 V     |
| Normal Resistance | 200 Ω   |
| Normal Inductance | 0.0028 H |
| Rotor Flux     | 0.2158 Wb |
| Number of poles| 4         |

Figure 2. The stator current waveforms under full load healthy condition.

Furthermore, BLDC motor has control switches circuit that use to sequentially energize the three-phase windings by power, consist of six switches as shown in Figure 3. The control signal related with voltage. Using a Simulink model in Figure 1, the phase voltage $V_a, V_b, V_c$ have been get equal 120V in three-phase in healthy condition as shown in Figure 4.

Figure 3. The electric control circuit of three-phase BLDC motor.
Bearing fault represents most faults occurring in BLDC motor about 40% [15]. Bearing consists of three parts inner race, outer race, and bearing ball as shown in Figure 5. In this work the vibration signals have been used as signature for mechanical fault.

Figure 5. The components of bearing in BLDC motor.

4. Gathering data for faulty condition

In short circuit fault, the imbalance in impedance in the stator windings will make the phase current and phase-to-neutral voltage asymmetries. The current signal will change its value and generate harmonics and high vibrations when fault occur, this lead to short circuit between the copper turns, due to increasing in harmonic generation and lead to insulation failures between the stator winding, so the surface area of winding will be large. Based on the equation 11, when area is large value, the resistance become small value.

\[ R = \frac{\rho L}{A} \]  

(11)

Where: R is the resistance value in the winding, (\( \rho \)) is the resistivity of the winding material, L is length of winding, A is the cross-section area of winding. when short circuit fault occurs in the motor , the current value will be very large and resistance value very small [16]. In this work, the short circuit fault has been performed in the model of BLDC motor by multiplying the rated resistance value in phase (a) by 0.2 % to make it very small value , and the inductance value has been determined in the stator winding, by using equation (12), as illustrated in Table1. The magnitude value of current has been illustrated in table 2. Figure 6 shows stator current waveform at short circuit fault condition.

Single phase open circuit fault causes overheating in the stator winding because the motor temperature increase. In open circuit fault, the current value is very small or zero and resistance value is very large [16]. In this work, the open circuit fault has been performed in the model of BLDC motor by multiplying the rated resistance value in phase (a) by 100 % to make it very large value , and the inductance value has been determined in the stator winding, by using equation (12), as illustrated in Table1. The magnitude value of current has been illustrated in table 2. Figure 7 shows stator current waveform at open circuit fault condition.

\[ \frac{R_{	ext{stator normal}}}{R_{	ext{stator fault}}} = \frac{L_{	ext{stator normal}}}{L_{	ext{stator fault}}} \]  

(12)[17]

Where: (\( R_{\text{stator normal}} \)) is the resistance of the stator winding at normal operation, (\( R_{\text{stator fault}} \)) is the resistance of the stator winding at fault operation, (\( L_{\text{stator normal}} \)) is the inductance of the stator winding at normal operation, (\( L_{\text{stator fault}} \)) is the inductance of the stator winding at fault operation.
winding at fault operation. Table 2 shows the resistance and inductance value at health condition, open circuit and short circuit fault condition, that have been determined as illustrated in above. Table 3 shows the peak value of current, that have been determined by change the resistance value at different cases.

Table 2. The resistance and inductance values in the stator winding at different cases.

| Faults case   | \( R_a (\Omega) \) | \( R_b (\Omega) \) | \( R_c (\Omega) \) | \( L_a (\text{H}) \) | \( L_b (\text{H}) \) | \( L_c (\text{H}) \) |
|--------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| Health case  | 200               | 200               | 200               | 0.0028            | 0.0028            | 0.0028            |
| Open circuit fault | 20000          | 200               | 200               | 0.28              | 0.0028            | 0.0028            |
| Short circuit fault | 40             | 200               | 200               | 0.00056           | 0.0028            | 0.0028            |

Figure 6. The stator current waveforms under full load at short circuit fault condition.

Figure 7. The stator current waveforms under full load at open circuit fault condition.

Table 3. The peak value of stator current at different cases.

| Stator current cases | No load | Half load | Full load |
|----------------------|---------|-----------|-----------|
|                      | \( I_a (\text{A}) \) | \( I_B (\text{A}) \) | \( I_c (\text{A}) \) |
| Normal               | 4.2     | 4.5       | 6.5       |
| Open circuit fault   | 0.14    | 11.11     | 11.16     |
| Short circuit fault  | 8.27    | 5.6       | 6.22      |

In this work, control switch fault has been performed by making the first switch open [2] as shown in Figure 8. The magnitude of phase voltages \( V_a, V_b, V_c \) equal 40V, 120V and 120V, respectively.
Figure 8. Simulation of control switches circuit at fault in switch 1.

The bearing fault experimental implementation of BLDC motor is very difficult because the required devices are not available. Bearing fault occurs as a result to increase the vibration. The database that represented healthy and inner race fault in bearing of BLDC motor has been get from acceleration sensor based on previous work [22], after this the data has been analyzed in MATLAB. The vibration signal from acceleration signal related with frequency, the small value of the frequency represented normal case, while the large value of frequency indicated to inner fault. In Figure 9, the vibration signal at no load inner fault condition has been plotted based on the data which has been get from another work [22]. Table 4 shows the kurtosis value which indicate to maximum amplitude of the vibration signal.

Figure 9. The vibration signal at no load inner fault condition.

Table 4. Kurtosis values for different load conditions.

| Bearing case       | Kurtosis (no load) | Kurtosis (half load) | Kurtosis (full load) |
|--------------------|--------------------|----------------------|----------------------|
| Normal             | 0.07               | 0.1                  | 0.13                 |
| Inner bearing fault| 4                  | 10                   | 21                   |

5. Neural Network for fault diagnosis

NN can be employed for the fault classification of BLDC motor. In this work, NN has been applied to classify normal operation, short circuit and open circuit faults in stator winding, control switch fault and bearing fault. The signal of three phase current, three phase voltage and kurtosis value forms seven input to NN, while the output is the required decision (healthy or short circuit or open circuit fault or switch fault or bearing fault). The performance of the NN was evaluated in terms of mean square error (MSE).

MSE was calculated using the below equation [16]:

\[
\text{MSE} = \frac{\sum_{p} \sum_{k} (d_{k}^{p} - y_{k}^{p})^2}{2p}
\]  

(13)

Where: \( p \) is the number of input patterns, \( k \) is the number of output neuron, \( d_{k}^{p} \) is desired output and \( y_{k}^{p} \) is network output for node. The first step of NN design is data modification, in this work, each set has been separated from other. The data has been classified into two sets: one is training set to
training process of the NN and other is testing set to test new data at various condition depend on training network.

The partition result of the database is:

- Training set contains 2835 rows (74%).
- Testing set contains 1000 rows (26%).

Feed Forward Back-Propagation (FFBP) is one of most used types of NN. FFBP training algorithm has been implemented with one hidden layer having 30 neurons, the neurons number in hidden layer has been selected based on trial-and-error method by enter number of neurons from 1 to 40 \cite{18}, (30 neurons) have been selected as the best number because the network performance has less error from other network with different neurons number \cite{19},\cite{20}. Figure 10 shows Neural Network layers constructed. The data in Table 5, Table 6 and Table 7 has been used to perform the training process, throughout the training operation of the network the weights are modified to get small error between actual output and target output. The training process stopped when reach maximum number of epochs or performance was minimized to the goal.

![Neural Network layers](image)

**Table 5. Artificial Neural Network Input training data at half load.**

| Operation cases       | \(I_a\) (A) | \(I_b\) (A) | \(I_c\) (A) | \(v_a\) (A) | \(v_b\) (A) | \(v_c\) (A) | Kurtosis value |
|-----------------------|-------------|-------------|-------------|-------------|-------------|-------------|---------------|
| Normal                | 4.5         | 4.5         | 4.5         | 120         | 120         | 120         | 0.1           |
| Open circuit fault    | 0.15        | 11.11       | 11.11       | 120         | 120         | 120         | 0.1           |
| Short circuit fault   | 9.5         | 5.6         | 5.6         | 120         | 120         | 120         | 0.1           |
| Control switch fault  | 4.5         | 4.5         | 4.5         | 40          | 120         | 120         | 0.1           |
| Bearing fault         | 4.5         | 4.5         | 4.5         | 120         | 120         | 120         | 0.1           |

**Table 6. Artificial Neural Network training data at full load.**

| Operation cases       | \(I_a\) (A) | \(I_b\) (A) | \(I_c\) (A) | \(v_a\) (A) | \(v_b\) (A) | \(v_c\) (A) | Kurtosis value |
|-----------------------|-------------|-------------|-------------|-------------|-------------|-------------|---------------|
| Normal                | 6.5         | 6.5         | 6.5         | 120         | 120         | 120         | 0.13          |
| Open circuit fault    | 0.16        | 11.16       | 11.16       | 120         | 120         | 120         | 0.13          |
| Short circuit fault   | 10.4        | 6.22        | 6.22        | 120         | 120         | 120         | 0.13          |
| Control switch fault  | 6.5         | 6.5         | 6.5         | 40          | 120         | 120         | 0.13          |
| Bearing fault         | 6.5         | 6.5         | 6.5         | 120         | 120         | 120         | 0.13          |

**Table 7. Target output.**

| Operation cases       | Target output |
|-----------------------|---------------|
| Normal                | 0             |
| Open circuit fault    | 1             |
| Short circuit fault   | -1            |
| Control switch fault  | 10            |
| Bearing fault         | 2             |
Figure 11. The flow diagram of Neural Network performance under mechanical fault.

Figure 12. The flow diagram of Neural Network performance under electrical fault.

The training process stopped when MSE arrives at $1.4425 \times 10^{-10}$ at 149 iterations with very low time has minimum gradient as shown in Figure 13.
Figure 14. Neural Network training regression.

6. Neural Network Result
The last step, network model has been tested to evaluate the effectiveness of the approach to classify the particular faults, Table 8 was used to achieve this purpose, Table 9 shows NN results at no load condition.

| Operation cases       | $I_a$ (A) | $I_b$ (A) | $I_c$ (A) | $V_a$ (V) | $V_b$ (V) | $V_c$ (V) | Kurtosis value |
|-----------------------|-----------|-----------|-----------|-----------|-----------|-----------|----------------|
| Normal                | 4.2       | 4.2       | 4.2       | 120       | 120       | 120       | 0.07           |
| Open circuit fault    | 0.14      | 10.7      | 10.7      | 120       | 120       | 120       | 0.07           |
| Short circuit fault   | 8.27      | 4.87      | 4.87      | 120       | 120       | 120       | 0.07           |
| Control switch fault  | 4.2       | 4.2       | 4.2       | 40        | 120       | 120       | 0.07           |
| Bearing fault         | 4.2       | 4.2       | 4.2       | 120       | 120       | 120       | 4              |
7. Conclusion
In this paper, NN has been proposed as the fault detection tools and is successfully used to detect and classify short circuit, open circuit faults in stator winding, control switch fault and bearing faults. Stator current, phase voltage and vibration signal provided a better indication about machines situation and are crucial for monitoring to improve reliability of the fault diagnosis process, where the network was operated with different conditions, five cases at half and full load have been used for training network and five cases at no load for testing network model.

FFBP algorithm was applied to classify both normal and abnormal conditions with high accuracy about (99%), correlation coefficient R is (1) and MSE equal (1.4425*10^-10) that make the NN model with the developed structure reliable for new operating conditions with less error.
It was demonstrated that the FFBP NN models gave more accurate results when compared with other network models. The training and testing results were almost nearer to the targets.

Table 9. Neural Network results at no load condition.

| Operation cases   | Fault diagnosis result |
|-------------------|------------------------|
| Normal            | 0.003                  |
| Open circuit fault| 1.01                   |
| Short circuit fault| -0.99                 |
| Control switch fault| 10                   |
| Bearing fault     | 1                      |

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