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Nonlinear Autoregressive with Exogenous Model to Diagnosis Open Switch Fault in PMSM

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Abstract:
This study aimed at presenting a technique to diagnosis faults of electronic switch in permanent magnet synchronous motor (PMSM). The current output of both thyristor bridges and the diode of system excitation is monitored under healthy and faulty operations. Features extracted at different operations using Multi-scale wavelet decomposition (MSWD). MSWD features are used to train Nonlinear Autoregressive with Exogenous Model (NARX) which sequentially operated to evaluate the fault level in case open circuit that developing across a switch. The two models have been tested and designed due to the simulated data, wherein the findings showed acceptable effectiveness in the diagnosis of various types of fault.
Keywords: *Neural Network , Fault Diagnosis , permanent magnet synchronous motor.*

INTRODUCTION

Electrical machines faults have been classified in into two groups: mechanical and electrical faults. To improve reliability levels of electrical machines, a robust condition monitoring are needed. Furthermore, it enables the avoidance of the replacement of parts and elements and heavy economic losses that responsible for stopped production. Therefore, this evoked the researcher to conduct this research and to design the modern fault diagnostics approach concepts [1]. The PMSM drive nowadays have found fast applications in industry. Applications like Machine gadgets drives electric vehicle propulsions and the systems of electromagnetic actuator. The system is consisted of a 3 levels machine accompanied by eternal magnet rotor supported by a DC source thru a3 levels inverter bridge, the capacitor of filter, and a chopper. The Chopper circuit two-quadrant hysteresis-kind is attached with a choke coil for the magnitude existing control.

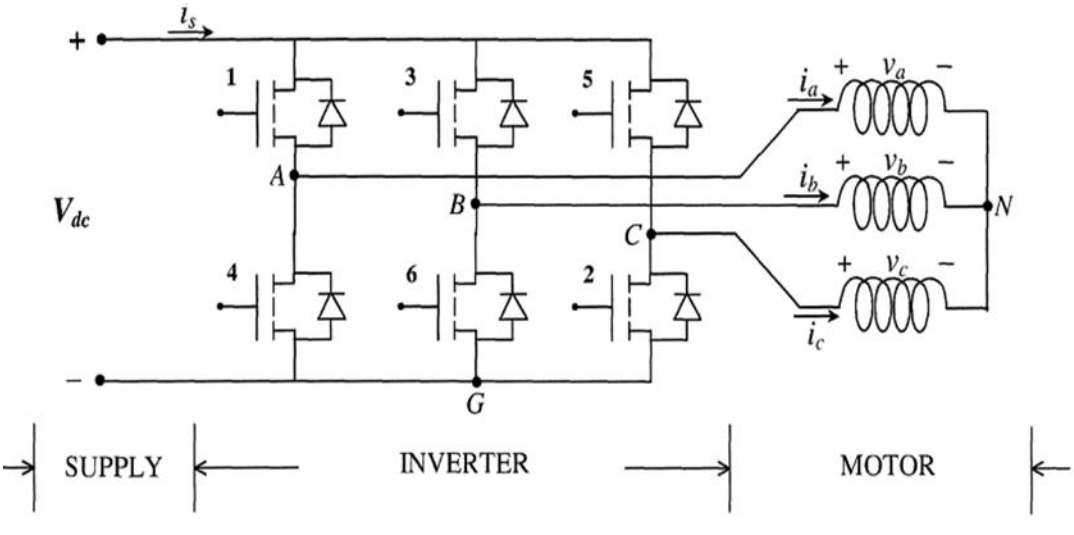

Figure 1 illustrates the integrated drive system’s schematic diagram.

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Various types of recognition approaches of electrical machinery were implemented for fault diagnosis and condition monitoring like signal processing, artificial intelligence (AI), hybrid techniques and model based. Nowadays, Artificial Intelligence is presented as an accurate technique regrading purposes of fault diagnosis and condition monitoring its been found that its hard to develop exact mathematical models. Th aim of artificial intelligence is to develop simple classifying expressions to be easily comprehended by people [2]. Artificial Intelligence contains methods based on genetic algorithms (GAs), fuzzy logic (FL) support vector machines (SVMs), adaptive neuro fuzzy inference systems (ANFIS) and neural networks (NNs) [4], With fuzzy logic, the merging algorithms are able to reduce the data driven fuzzy [3]. Moreover, fuzzy models helps in adapting their structures and parameters and interpretability over time [5][4].

NNs considered as global approximations, it's able sometimes to represent high degrees of nonlinearity occurred within the data than FL specifically, during the utilization of time-delayed characteristics regards training. Furthermore, models of FL rely on rule explosion, for example, exponentially, the increase of number of rules depends on the variable increases of the fuzzy sets or number of variables, leading to a complexity identifying the total model based on expert knowledge only [6]. On the other hand, based on its affective characterizations abilities, the support vector machine (SVM) is considered as an effective tool for the classification of motor fault due to the statistical learning theory [7]. The normal support vector machine is rely on binary categorisation issues to identify a linear boundary among the two various types, by maximizing the space of the closest data to the boundary in every class. Nonetheless, a support vector machine requests kernel parameters' rigorous tuning and maximizing generates a huge quantity of calculation. In addition, support vector machine needs a extensive range of data and contains high complexity, the normal support vector machine is of no use with dynamic data [8]. NN has been considered as an effective method for the detection of motor fault. This techniques doesn't require a mathematical model. Moreover, NNs are able to identify patterns despite the high levels of noise [9]. Past studies, through the review of the literature, has used the static NNs to classify faults, whereas many of the industrial systems, in nature, are nonlinear and dynamic. Therefore, when identifying the fault, studies have employed the methods able to show the dynamics of the system. NARX development has received great attention to due to its capability for generating nonlinear dynamical systems. The study [2] revealed that for fault diagnosis in electrical machines, NARX could be the most effective technique. NARX allows enhanced accuracy prediction of fault of systems monitoring condition that considered to have extra effect than static NN. Moreover, DRNNs provide the capability to learn the dynamics of complicated nonlinear system and more versatile as conventional static NN proved to not have this kind of capability [10]. The current study aims at diagnosing switch open-circuit faults of the inverter bridge during forward motoring, as it is been acknowledged as a popular mode of operation. The supply short circuit will take place in case the short circuited of MOSFET. On the other hand, at the normality of switching pattern, it should trip such a fault. At the time of forwarding motoring, due to the logic signals of three rotor-position Hall sensors, switches will turn ON and OFF. Switching happens in a way that increases the torque improved due to magnetic communication among rotor fields and stator [13].

Fault Diagnosis Process

Procedures of the suggested diagnostic utilized in this current study contain three main phases, as showed in Fig1. In first phase, the collection of the physical current occurred, then MSWD has been utilized to excerpt the frequency domains and the beneficial characteristics in time. Next, the features will be reduced utilization, the phase of feature reduction is most critical phase in the process of diagnosis. A tool with inaccurate reduction feature has the ability jeopardise the overall performance and has the possibility to delete beneficial information. The last phase is to classify fault thru the use of NARX.

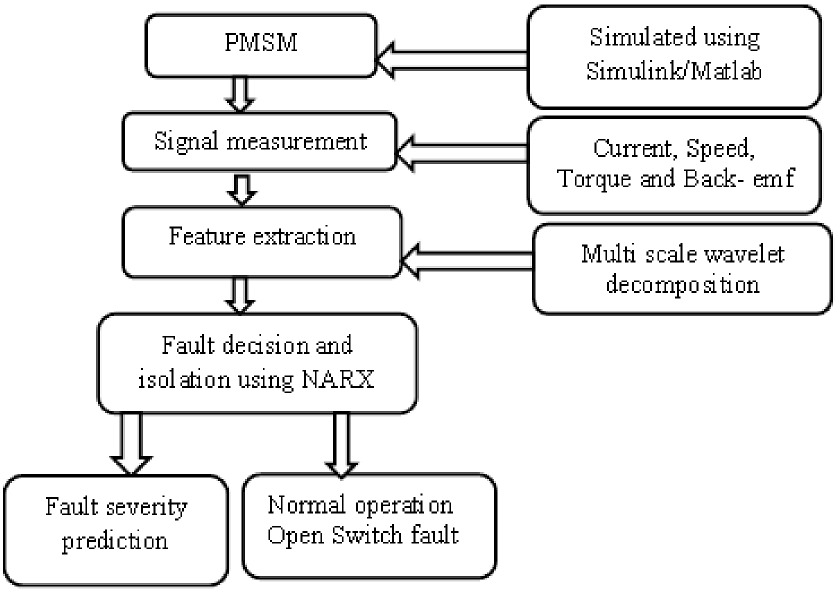

Figure 2 Fault Diagnosis Process

1. Simulink Model of PMSM

This paper assumes a compromise among model accuracy and computational complexity. The versatile model developed in the current study is representing the PMSM faulty and healthy condition. The researchers made some assumptions during the design process of the model [13]:

Ignore the motor cogging torque.

The induced harmonic in the rotor due to stator harmonic fields are ignored

The iron and stray loses are also neglected

Saturation is neglected

Voltage drop across the electronic control circuit are negligible

Eddy Current and hysteresis loses are neglected

The PMSM system is defined by the following equations:

$$V_{abc} = I_{abc} + + R_{abc} + \frac{dh_{abc}}{dt} + e_{abc} \quad (1)$$

$$h_{abc} = L_{abc} + I_{abc} \quad (2)$$

$$L_a = L_a = L_c \quad (3)$$

$$L_{s=} L_{m=} L$$

(4)

The stator phase voltage equation is given by:

$$\begin{bmatrix} V_a \\ V_b \\ V_c \end{bmatrix} = \begin{bmatrix} R_a & 0 & 0 \\ 0 & R_a & 0 \\ 0 & 0 & R_a \end{bmatrix} \begin{bmatrix} I_a \\ I_b \\ I_c \end{bmatrix} - \begin{bmatrix} L_s & L_m & L_m \\ L_m & L_s & L_m \\ L_m & L_m & L_s \end{bmatrix} p \begin{bmatrix} I_a \\ I_b \\ I_c \end{bmatrix} - \begin{bmatrix} e_a \\ e_b \\ e_c \end{bmatrix}$$

(5)

The electromechanical torque generated by the motor is expressed as:

$$T_{em} = J \frac{d_{wr}}{dt} + \beta w_r + T_l$$

(6)

Speed of motor is proportional to the position of the rotor and given by:

$$\frac{d\theta}{dt} = w_r \quad (7)$$

Where, T_l is the load torque and e_{abc} is the back–emf, γ_{abc} is flux linkage, R_{abc} is stator resistance, L_s is self-inductance, V_{abc} is three phase voltage, , I_{abc} is three phase stator current, w_r is a rotor speed, e, L_M is a mutual inductance, L is inductance, T_{em} is an electro mechanical torque, θ is an electrical position of the rotor flux.

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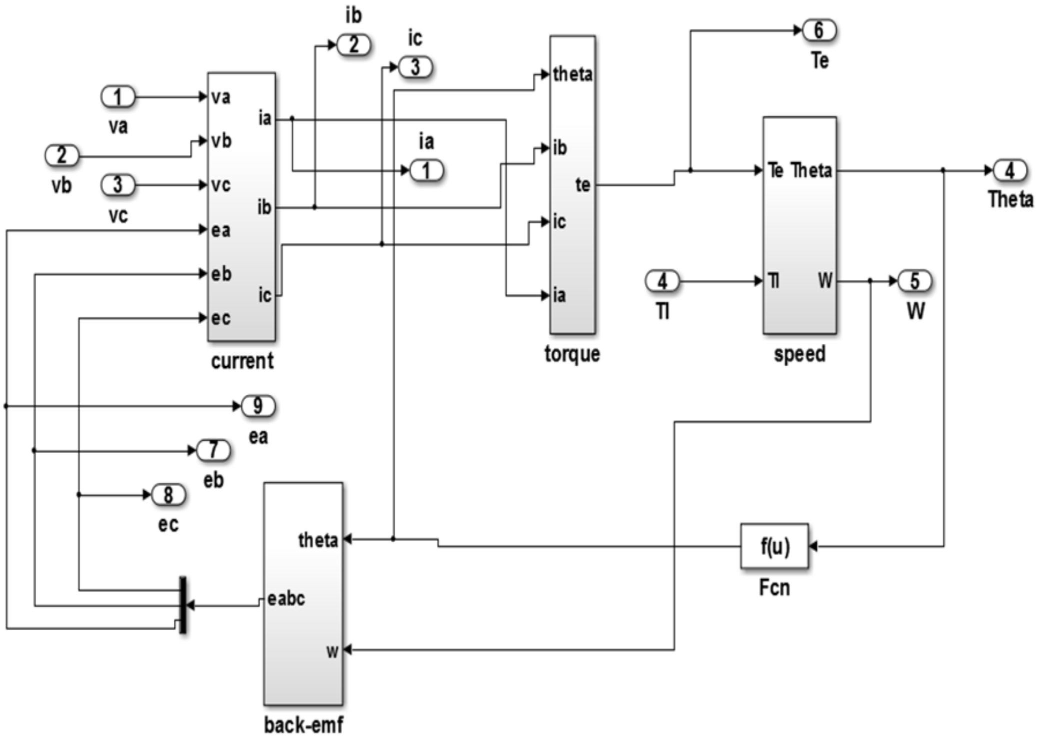
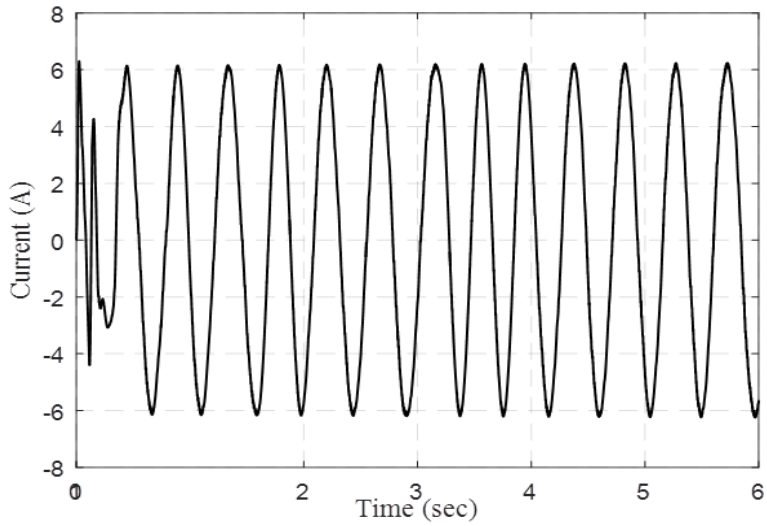


Figure3.Simulink diagram of a process

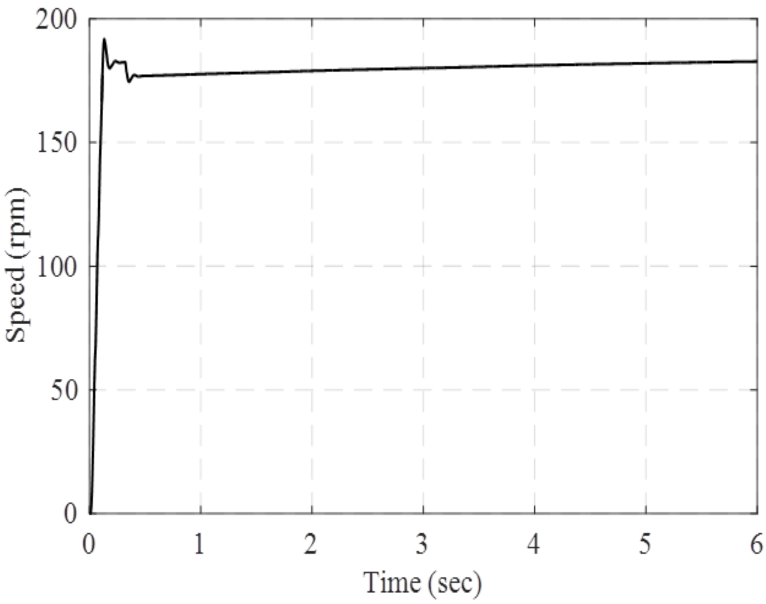
PMSM equations are simulated using Matlab/Simulink environment with SimPower system toolbox. Figure 3 shows the overall block diagram of the PMSM drive. It is divided into different functional blocks PMSM, current control, power inverter, speed control and reference current. The inputs for references current block are the current signal and position signal (θ). The reference current block produces three phase reference current as input to current control module. The speed can be controlled in closed loop by measuring the real rotor speed and comparing with reference speed. Reference current block will produce reference current for current control block so that the motor torque will change depending on reference current amplitude. Current control block compares three input phase current with a reference current signal and then pass the output control signal to the sequence driver block which includes MOSFET-based three-phase bridge inverter/converter circuit. PMSM consists of two parts: one is an electrical part defining electromagnetic Torque (T_{em}) and a phase current of the motor and the other is a mechanical part generating motion of the motor. The inputs to PMSM block are terminal phase voltages and load torque. The PMSM contains several sub blocks such as back-emf, current, speed, and torque [15].

4.PMSM switch performance at Normal and abnormal operation

waveforms of performance features have been observed in standard operation of the system with stable speed. This type of operation contained imperfect and perfect contacts and other conditions like noisy operating. The perfection of inverter bridge's electronic commutation occurs when the transition among switching states gives exact wanted positions of rotor. This condition has been categorized as the best normal operating condition. Fig. 4 through 5 shows characteristic current waveforms at 200 RPM at normal operation condition.



(a)



(b)

Figure 4. PMSM performance under healthy condition (a) current, (b) speed

The model represented each electronic switch the drive system was thru nonlinear resistor, nonlinear resistor gains a very low value If the switch is ON, on the contrast, the value is very high if it is OFF. At the normal switching pattern, short circuit across any switch leads to a supply short circuit. This should be tripped by the supply over-current protective relay. The researcher modeled the switch open-circuit faults by giving the nonlinear resistor an extremely high value representing the faulty switch. Healthy MOSFET could be switched ON within 2 consecutive states, i.e., “one third of the whole electrical cycle”. Features of Performance have been observed in open-circuit faults thru all the switches of MOSFET: one at a time. These features have been compared to the waveforms of normal operation to acquire a group of diagnostic indices. Fig 5 shows the Motor DC-link currents accompanied by open circuit faults thru switches 1**,** Thus, stage **A** doesn’t have positive current at all, under an open circuit fault on switch 1, Also the rest of stages don’t have

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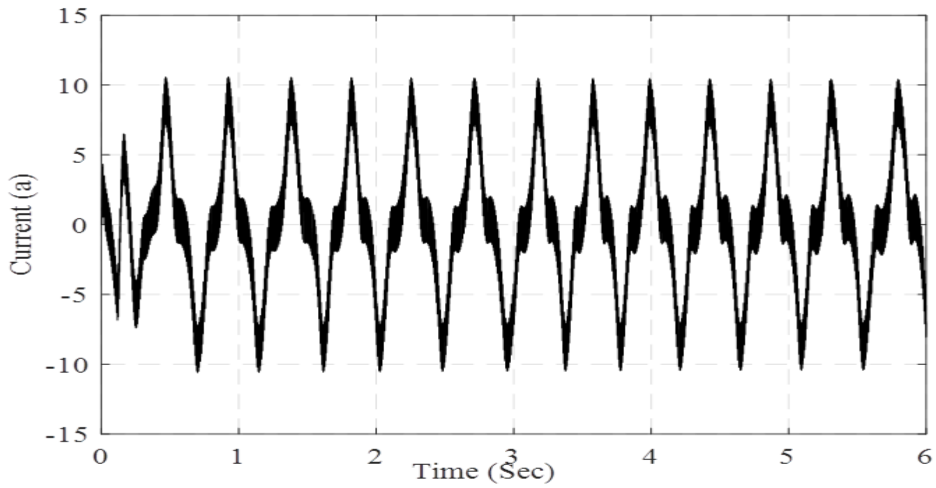
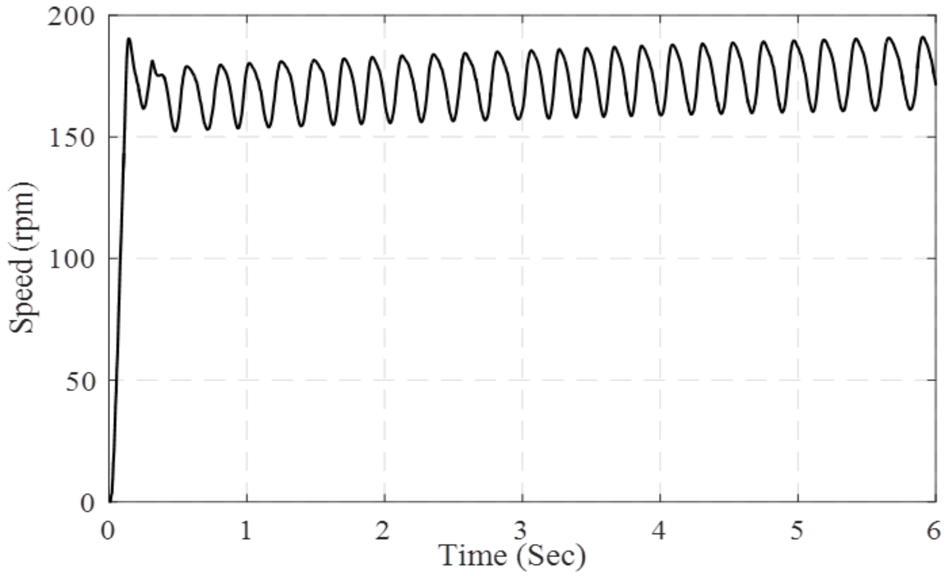
negative currents during switching states 1 and 6 respectively [15,16] (see fig 6).



(a)



(b)

Figure 5. PMSM performance under faulty condition (a) current, (b) speed

Recently, new chapter of Multi wavelet was added to the theory of wavelet. As in the wavelet case, they are considered to be vector-valued wavelets which satisfy conditions as they involve matrices instead of scalars. This can be a benefit, as it may construct multi-wavelet bases which has various possessions simultaneously. For instance, symmetry and orthogonality, high number of and short support of vanishing moments. Multi-resolution analysis concept is able to be maximized to general dimension starting from the scalar case N. A vector valued function $\lfloor \emptyset_{,1} \emptyset_2 \dots \dots . \emptyset_2 \rfloor^T$ belongs to $L^2(R^r)$ and N is multi-scaling function if the sequence of closed spaces [17, 18]

$$V_j = \{span 2^{j/2} \emptyset_{i(2^{j-k})} : 1 \leq i \leq r, k\epsilon z\}$$
(8)

signal decomposition $x(t)$of full multi wavelet could be reached thru the scaling coefficient iterative filtering as follows:

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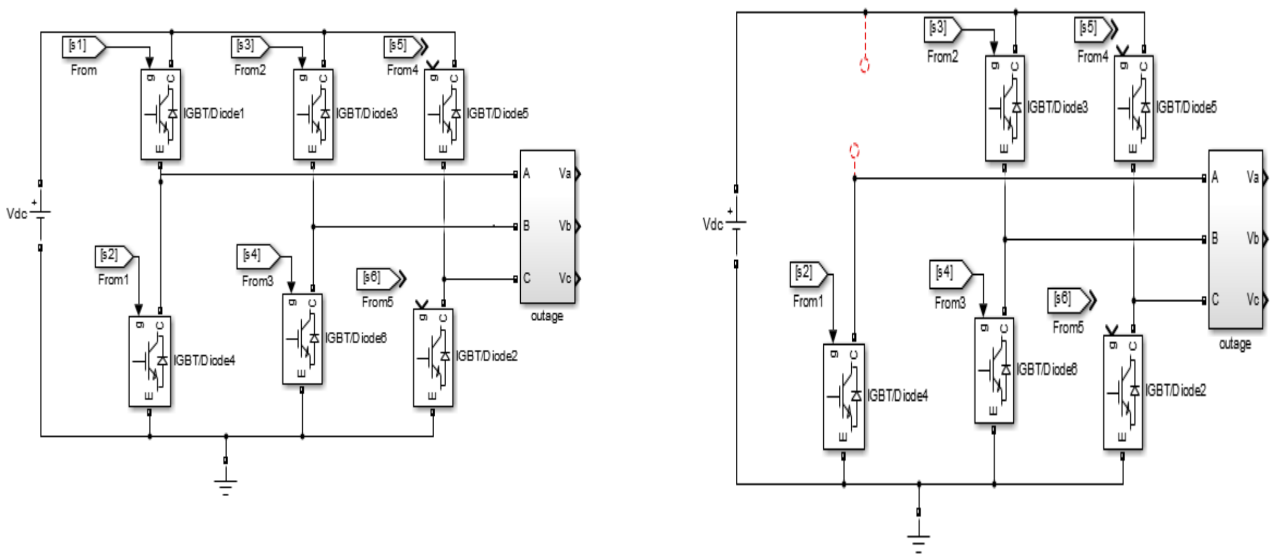
$V_{jk} = \sum G_m - 2kV_{j-1,m}$ (9)

$W_{jk} = \sum H_m - 2kV_{j-1,m}$ (10)

Where V_{jk} , W_{jk} are $r \times 1$ column vector



(a)

(b)

Figure 6. PMSM control circuit at (a)healthy (b) faulty conditions

NARX is a model of nonlinear autoregressive that possess exogenous inputs. Meaning that it connects the existing value of a time series to:
Previous values of the similar series.
Previous and existing values of the exogenous (driving) series which is of the outwardly identified series that impacts the interest series.
That is connected to the fact that knowing the rest of terms doesn't give the ability to predict the current values in times in exact way. This model could be written algebraically. *U* is the externally determined variable; *y* is the interest variable. Therefore, based on this equation, information about *y* can be predicted thru the information of *u*, as do previous values of *y* itself.

Table. 1 introduce the parameters of NARX which were applied at the time of training process.
Utilizing little neurons in the hidden layers results to detect the signals adequately in a complex data set. On the other hand, utilizing a lot of neurons in the hidden layers gives over fitting. This over fitting located if the NN contains many information processing capacity where contained inadequate amount of information within the training set is not able to train the whole number of neurons in the hidden layers. Moreover, the required time to train the network can be extended by the inordinately huge number of neurons within hidden layers. In order to improve the suitable number of hidden neurons, error steps and several trial have been utilized.

Table1. NARX training parameters

Learning rate (α)	Regularization parameter(λ)	I ratio	No of Delay	No of iteration	No of Hidden unit
0.1	0.001	0.7	6	3000	25

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results show that classification accuracy mean that utilized the suggested technique is 97% indicating that it's remarkable better than the current used approaches. A plethora of studies use one signal only to indicate the fault which leads to limit the accuracy in classifying the faults' severity (see fig 7).

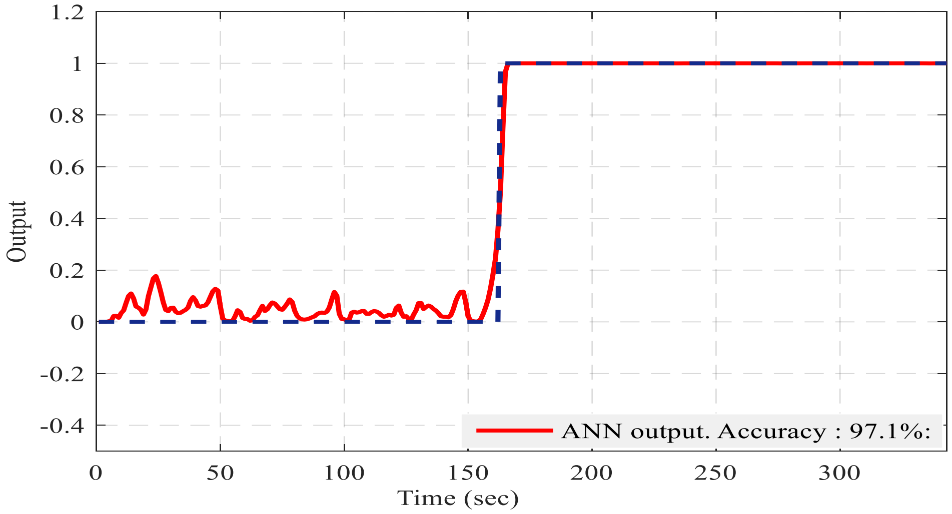

Figure.7 NARX performance

Conclusions

This study developed a Model of Nonlinear Autoregressive with Exogenous (NARX) to diagnose open-switch fault of the inverter bridge of PMSM drives. performance characteristics of the system either faulty or healthy are gained through a discrete-time lumped-parameter network model. The study derived the diagnostic indices from current signal of the motor DC-link after it was treated by wavelet transform. These indices represented the averaged coefficients of MSWD over the six time-windows' middle halves related to the inverter bridge's six switching states. An intelligent paradigm, NARX trained based on diagnostic indices acquired from different conditions of operation.

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