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Robust Fault Diagnosis in Electric Drives Using Machine Learning

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***Abstract*– The power electronics inverter can be considered as the weakest link in an electric drive system, hence the focus of this research work is on the detection of fault conditions of the inverter. A machine learning framework is developed to systematically select torque-speed domain operation points, which in turn are fed to an electric drive model to generate signals for training an artificial neural network that has the capability of robustly classifying multiple classes of faults in the electric drive system. Six faulted models for the inverter and the motor, and a normally functioning model were used to generate various fault condition data for machine learning. The technique is viable for accurate, reliable and fast fault detection in electric drives.**

***Keywords*-- model-based diagnostics; power electronics; inverter; motor; electric drives; neural network; electric vehicle; hybrid vehicle; field oriented control.**

I. INTRODUCTION

The automotive industry has been paying significant attention for over a decade on electric vehicles (EV) and hybrid electric vehicles (HEV) [1,2]. These vehicles help reduce harmful emissions and also contribute to fuel economy. The main components in these vehicles are the electric drive and the power electronics based inverter, together with the necessary control system. The trend in the industry is to use 3-phase induction motor for the electric drive, which is considered to be a very robust motor [1,2]. Precise torque control of induction motor can be done by power electronics inverter based Field Oriented Control or FOC [3-8] techniques. An electric drive can malfunction depending on whether the inverter or the motor is faulty. The motor, however, is a more robust device compared to the inverter. Hence, in this work we will focus primarily on the inverter problems.

In a separate paper [9], the authors have described techniques to locate the fault in an inverter system. There the authors used a model of the power electronics based inverter and the 3-phase induction motor (see Figs. 1 and 2) along with its control system by using the Matlab-Simulink software to generate various simulated signals under normal and faulted conditions of the inverter switches. The signals collected at different torque-speed operation points were fed to an ANN (artificial neural network) based learning algorithm to detect faults and their location. In [9], the choice of torque-speed points was arbitrary. In this work a systematic methodology based on machine learning is developed to select effective operating points in the torque-speed domain to generate training data for training the ANN. We will show that the ANN trained on data generated by the operating points selected by the proposed algorithm is more robust in fault classification for any given torque/speed condition.

II. PROBLEM SPECIFICATION

For a 6-switch inverter driven 3-phase induction motor (see Figs. 1 and 2), we use the pulse width modulation technique to realize the voltage reference command [8]. Obviously, if the switches fail to function in the way it was intended to, the voltage synthesis process will be impaired, and hence will fail to obtain the requisite torque at the motor shaft. The failure of the switches can take place in the form of "open circuit" or "short circuit" faults. The reverse diodes in the switches can fail too, although we will focus in this work on the forward switches, in order to illustrate the methodology without loss of generality.

In this 6-switch inverter system, there are m given current sensors $\{I_j \mid j = 1,\cdots,m\}$ in the output inverter lines, and n voltage sensors $\{V_l \mid l = 1,\cdots,n\}$ across the lines, and the torque-speed operating points (Tq, Sp) are control parameters in the torque-speed space S, that reflect the system operational condition. Different torque-speed operating points (Tq, Sp) generate different operating voltages and currents under both normal and faulted conditions. Hence, in order to identify a fault over a wide range of torque-speed domain, it is necessary to make a system learn the fault behavior over an effective range of torque-speed conditions.

The fault diagnostic problem for the 6-switch inverter driven 3-phase induction motor is to identify the faulty inverter switch among the six switches ($W_1, W_2, \cdots, W_6$). At this stage, we assume that only one out of six switches can fail at a time.

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14. ABSTRACT
The power electronics inverter can be considered as the weakest link in an electric drive system, hence the focus of this research work is on the detection of fault conditions of the inverter. A machine learning framework is developed to systematically select torque-speed domain operation points which in turn are fed to an electric drive model to generate signals for training an artificial neural network that has the capability of robustly classifying multiple classes of faults in the electric drive system. Six faulted models for the inverter and the motor, and a normally functioning model were used to generate various fault condition data for machine learning. The technique is viable for accurate, reliable and fast fault detection in electric drives.

15. SUBJECT TERMS
model-based diagnostics; power electronics; inverter; motor; electric drives; neural network; electric vehicle; hybrid vehicle; field oriented control.

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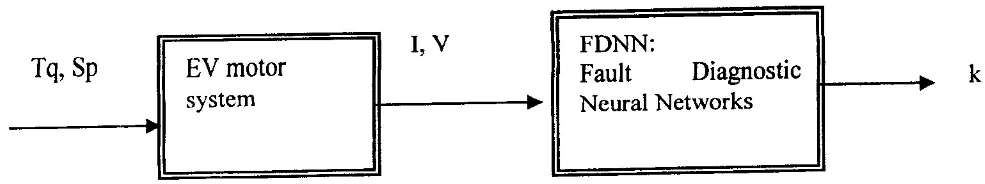

Figure 4. Fault diagnostics of EV motor system using a well-trained neural network

Fig. 3 illustrates the proposed machine learning framework for a robust EV diagnostic system. An algorithm, CP-Select (Control Point-Select), has been developed for systematically selecting representative control points in a given parameter space. The selection is based on the performance of the neural network which is trained using the data generated by a set of control parameters. The performance of the neural network is evaluated using a validation data set, which is randomly selected from the parameter space. The selected control parameters are used by a simulation model that simulated the functions of the EV motor system and outputs the current and voltages. These signal data are sent to feature extraction and neural network training. The system finishes the learning process when the evaluation of the trained neural network satisfies a chosen criterion. The result of this machine learning process is FDNN (**F**ault **D**iagnostic **N**eural **N**etwork), a neural network that has the capability of detecting faults of the component EV motor system as illustrated in Fig. 4, where k indicates either normal condition or a type of fault. We usually take multi-class MLP networks as FDNN, and the activation function of every node in FDNN is assumed to be sigmoid function [10].

The core algorithm in the machine learning framework is implemented through the CP-Select algorithm, which goes through a coarse-to-fine subspace division. For each parameter space, the CP-Select algorithm goes through the four step operations: (a) parameter selection, (b) training data generation, (c) neural network training, and (d) performance evaluation steps. The algorithm continues these four steps for finer subspaces until the performance of the newly trained neural network, FDNN, satisfies the performance criterion. Generally, CP-Select algorithms just select those typical points like corner or centers points (parameters) in the control parameter space. New training data are generated based on those selected points and are added into training data set for neural networks training. After that, the performance on validation points determines which subspace will be chosen for next step parameter selection.

The detailed description of CP-Select algorithm is as follows.

First we define the control parameter space, S, by the ranges of valid values of these parameters. Note, the CP space S can be higher than 2-dimensional, although in the EV motor diagnostics application, we deal with two dimensions, torque and speed. We will use Fig. 5 to assist in the description of the CP-Select algorithm. The CP-Select algorithm uses the following variables:

Para-list: a list containing all the control parameters used to generate the current training data. Initially, Para-list is set to nil.

T_v: a validation set that contains parameters randomly chosen from the CP space S for evaluating the performance of the newly trained neural network.

Perf_th: this is the performance threshold used as the stopping criterion of the algorithm.

Tr: training data generated by the simulation model using the control parameters in Para-list. It is initially set to nil.

NN: a neural network that detects multiple classes of faults.

CP-Select Algorithm:

Step 1: Initialization.

1.1 Randomly select m parameters from S and store them in T_v.

1.2 $\Phi = \{S\}$, para_list = {},

Step 2: Remove the first parameter space from Φ and set it to C_CP . Initially, C_CP =S.

Step 3: Choose the 4 corner points of C _CP, X_1, X_2, X_3 and X_4 and the center point X_5 (see Fig. 5 for illustration.) Let P_0 be = $\{X_1, X_2, X_3, X_4, X_5\}$, and num_select = 1

Step 4: $P_1 = P_0 - P_0 \cap para\_list$.

4.1 If P1 is empty and num_select =1 go to step 7.

4.2 If P1 is empty and num_select =2 go to step 9.

4.3 If P1 is empty and num_select =3 go to step 11.

Step 5: Send every parameter in P_1 as input to the simulation model of the EV Motor system shown in Fig. 3 to generate a training data set Tr_0, which consists of various voltage and current signals.

Set Tr = $Tr \cup Tr_0$. Now the training data consists of all the voltages and current signals generated by the simulation model by using all the parameters on the para_list.

para_list = para_list $\cup$ P1.

neural network is used as FDNN, and the neural networks architecture is 42-20-7 (42 input dimensions, 20 hidden nodes and 7 output dimensions). The experiment went through 3 iterations described in the CP-Select algorithm and generated three training data sets marked out in Fig. 11.

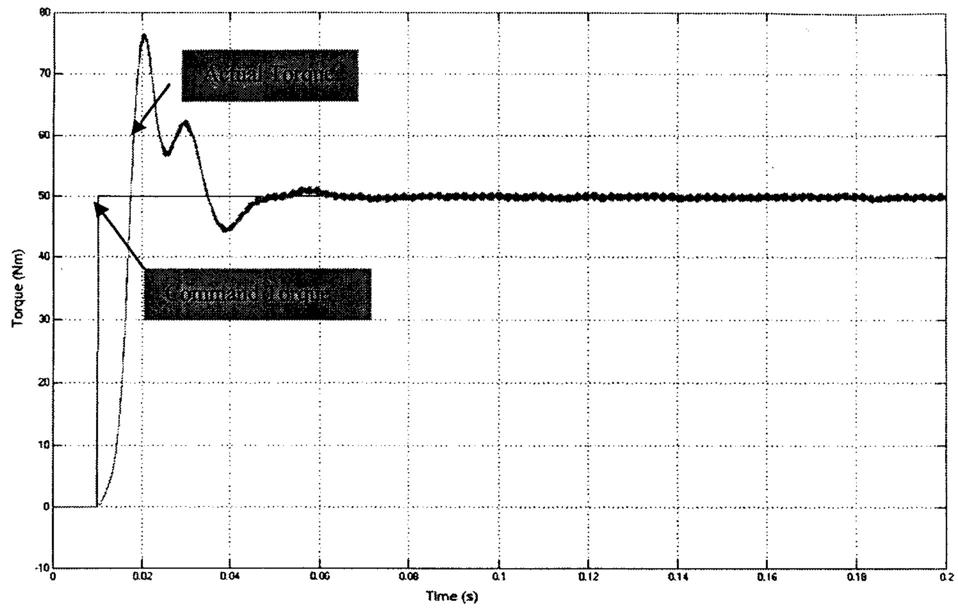

Figure 6. Torque signal in the normal condition in a sine-PWM-closed-loop model

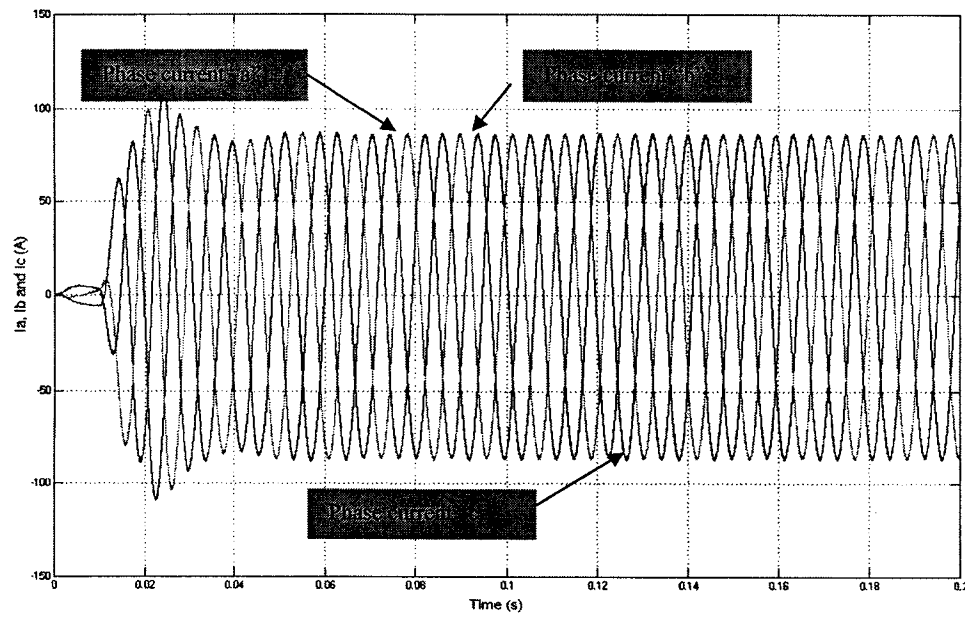

Figure 7. Ia (green), Ib (red) and Ic (blue) signals generated by a sine-PWM-close-loop model in a normal operation condition.

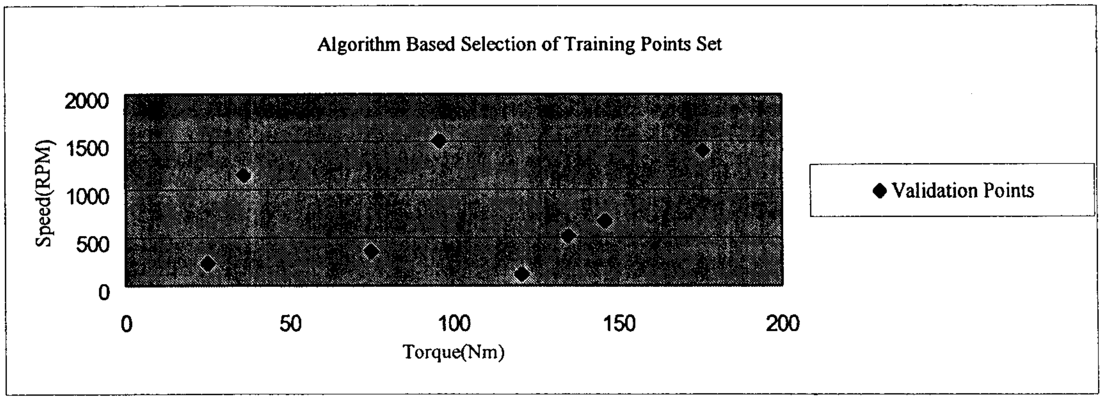

Figure 10. Validation Points used in experiment.

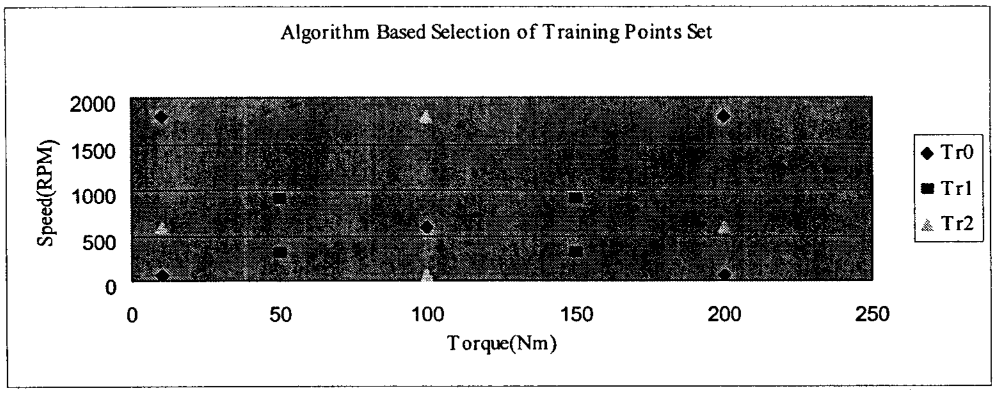

Figure 11. Train points generated by the CP_Select algorithm during the first three iterations.

The performance of the neural network FDNN trained on the data generated by Tr_0 on Tv is presented in Table I. The overall performance is 94.62% < Perf_th=99%.

At the second iteration, the performance of the neural network FDNN trained on the data generated by $Tr_0 \cup Tr_1$ on Tv is presented in Table II. The overall performance is 96.06% < Perf_th=99%.

At the third iteration, the performance of the neural network FDNN trained on the data generated by $Tr_0 \cup Tr_1 \cup Tr_2$ on Tv is presented in Table III. The overall performance is 100% > Perf_th=99%, therefore the algorithm stops here.

TABLE I. THE PERFORMANCE OF FDNN TRAINED ON DATA GENERATED BY PARAMETERS IN Tr_0.

	Correct Rate (%)
Normal	83.86
Fault 1	95.82
Fault 2	98.34
Fault 3	100
Fault 4	95.89
Fault 5	93.40
Fault 6	95.13
Total	94.62

TABLE II. THE PERFORMANCE OF FDNN TRAINED ON DATA GENERATED BY PARAMETERS IN $Tr=Tr0 \cup Tr1$

	Correct Rate (%)
Normal	85.55
Fault 1	92.18
Fault 2	98.90
Fault 3	98.61
Fault 4	99.49
Fault 5	97.50
Fault 6	100
Total	96.06

TABLE III. THE PERFORMANCE OF FDNN TRAINED ON DATA GENERATED BY PARAMETERS IN $Tr_0 \cup Tr_1 \cup Tr_2$

	Correct Rate (%)
Normal	100
Fault 1	100
Fault 2	100
Fault 3	100
Fault 4	100
Fault 5	100
Fault 6	100
Total	100