On-Line Switch-Open Fault Detection of PMSM Using Artificial Neural Network

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***Abstract*—This paper proposes an artificial neural network which can detect a switch-open fault in PMSM. The proposed method does not require any post-processing of the data for fault diagnosis. Also, using the electrical property of the fault, the required number of neuron in the input layer is only 12, so the DSP may perform on-line analysis of the system. The training dataset is obtained through wide operation area considering errors in parameter values. The proposed artificial neural network could classify the status of the machine correctly unless there is zero-speed crossing moment. A fault diagnosis governor concept is introduced, which is to utilize the ANN based on the speed of the machine, and the ANN became able to give right answers all the time. The proposed method was also verified with an experiment, and a switch open fault occurred during the operation could be detected.**

***Index Terms*—Fault detection, fault classification, artificial neural network, supervised learning**

I. Introduction

Nowadays, electric machines are found in various fields in which they have many roles. Thanks to their high power density and wide operation range, applications are becoming smaller and convenient. However, there exist many kinds of faults in an electric machine that could make the whole system be in danger. Some faults are fatal so that the inverter should handle them immediately and stop the machine. However, there are some non-fatal faults which cause torque distortion in the drive where the machine 'still can' be operated; a switch open fault is included in these faults. If the fault is found and classified by the inverter in such case, the user can handle the situation simply and correctly.

The basic fault detection method is to measure the currents or voltages of a machine while operating the machine in a specific condition and to compare them with the pre-investigated information [1], [2]. This kind of approach requires a large look-up table (LUT) for the algorithm. On the other hand, there are studies proposing fault-indicating schemes based on electrical properties of the machine [3]–[5]. However, the above methods highly depend on the parameters of the machine so that they may give wrong diagnosis results.

Nowadays, machine learning is broadening its application, and fault detection in an electric machine is one of the fields under the limelight [6]–[9]. Fault detection of an electric machine is being covered with various forms of artificial intelligence, from *k*-nearest-neighbor (KNN) algorithm to a neural network. However, these methods have requirements on fault diagnosis; some researches used data gathered at the specific operating condition, and other studies utilized a relatively large number of data with post-processing of Fourier transformation. Such methods restrict the environment of fault diagnosis so that the faults cannot be found during the operation, which means that systems with no self-checking stage cannot find their defects and get fixed.

In this paper, an on-line switch-open fault detection method is proposed, which can be applied at any operating points and can tell which switch is damaged. The proposed artificial neural network (ANN) or probabilistic neural network (PNN) gives 7 probabilities of 1 normal condition and 6 fault conditions, so a controller can classify the situation of the system. The network is composed of a small number of nodes (and weights) so that a DSP with limited computational power and memory can also carry out fault-diagnosis. It was implemented based on the fact that the voltage error, the voltage difference between the current controller output and the one obtained from current measurement, under switch-open fault condition is highly related to the 6th harmonics of electrical angular speed. In other words, an effective sampling method was proposed for switch-open fault detection. The proposed method is verified with simulations. Moreover, some occasions that ANN may give wrong classification results are introduced, and the corresponding solution (fault diagnosis governor concept) is proposed.

II. ANN for Fault Classification

A. Why Machine Learning?

The biggest reason for using machine learning for analyzing a system is that artificial intelligence may figure out a (nonlinear) relationship between the inputs and outputs, which could not be noticed by the system designer's instinct. In this paper, the classifying tool should tell the status of the motor from 'some information' that is related to the motor status. This kind of problem is called 'classification', which is one major field of supervised learning. The choice of the information is important for the performance of the classifying tool, thus a designer must have proper understanding about the system so that good 'labeled dataset' can be generated, which is the set of inputs and outputs(statuses). Usually, *k*-

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TABLE I
STATUSES OF INVERTER FOR PMSM DRIVE

#	Status
1	Normal
2	Fault – A phase upper switch open
3	Fault – A phase lower switch open
4	Fault – B phase upper switch open
5	Fault – B phase lower switch open
6	Fault – C phase upper switch open
7	Fault – C phase lower switch open

TABLE II
BASE SPEED AND BANDWIDTHS OF SYSTEM IN SIMULATION

Parameters	Values
ω_{base}	1000 rad/s
$f_{c,ctrl}$ (current controller)	500 Hz (3142 rad/s)
$f_{s,obs}$ (speed observer)	20 Hz (126.7 rad/s)
$f_{s,ctrl}$ (speed controller)	5 Hz (31.42 rad/s)

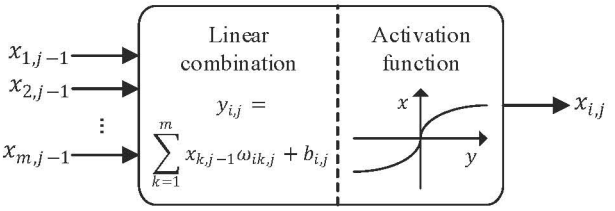

Fig. 1. Output calculation of the ith neuron in a jth layer when the j-1th layer has m outputs. All outputs, z_i's, are again connected to all neurons in j+1th layer. Goal of ANN training is finding all ω's and b's for a given dataset.

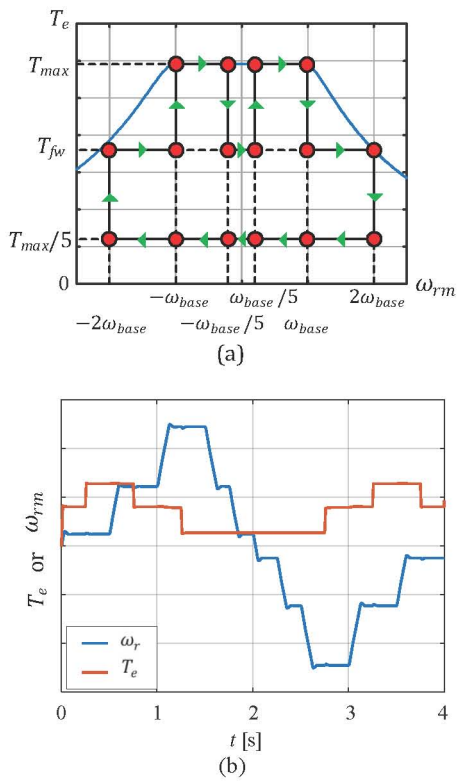

Fig. 2. (a) Capability curve of the machine with operation profile for obtaining the ANN training dataset and (b) normal operation waveform.

nearest neighbor (KNN), decision tree (DT) and ANN methods are used for a classifying problem. In this paper, an ANN is selected for analyzing the status of the motor, and it is trained to give probabilities of each status. An ANN is composed of layers which include neurons in it. Each neuron have input values and output values. Except the neurons in the 'input layer', the input value of a neuron becomes the linear combination between all output values of prior layer and corresponding weights. Then the output of the neuron is obtained by passing the input value to the activation function. This is shown in Fig. 1. Detailed training and classifying methods are introduced in the next section.

As the fault situations can be studied with mathematical approaches based on the voltage equations of the electric machine, someone may check the status of the electric machine by sampling the voltage errors at specific positions and comparing it with the preliminarily investigated values. However, such method requires many judging statements in the implementation, where parameters should be precisely-known for wide operating range; hence large calculation overhead and memory. Moreover, if the system should detect various kinds of faults, the calculation required for analyzing the machine status would be multiplied by the number of kinds. Errors in the known parameters will be another problem for this approach.

On the contrary, if an ANN is trained for wide operation range where errors of machine parameters are considered together, the ANN can distinguish between the statuses with no complicated judging statements. The ANN always receives the same input variables and do the same (forward propagation) calculation for finding out the probabilities of the statuses.

B. Obtaining Dataset for ANN

In this paper, the goal of an ANN is to give 7 probabilities for different statuses listed in Table I. The ANN is generated for the diagnosis of a torque-controlling motor where the normal load machine controls the speed.

If an inverter has an open switch, the output voltage would be different from the intended one of the current controller. This difference can be measured by calculating the applied voltage using the sensed currents and known parameters. These values become the inputs of the ANN in this paper and are noted as $V_{dqsr,err}$. As the voltage output errors are composed of harmonic waves of electric angular speed, it is better to sample the voltage error at the fixed positions, not with the fixed sampling time. In this paper, $V_{dqsr,err}$ values are sampled every $\pi/3$ angle, from the position when the magnet is aligned along A phase, so 12 input data are generated every electric cycle. Dataset is made by recording recent 12 $V_{dqsr,err}$ values with corresponding status of the machine.

Fig. 2(a) depicts the capability curve for certain parameters used for simulation. In this paper, it is assumed that the parameters of the machine do not change according to the operating point. However, if the

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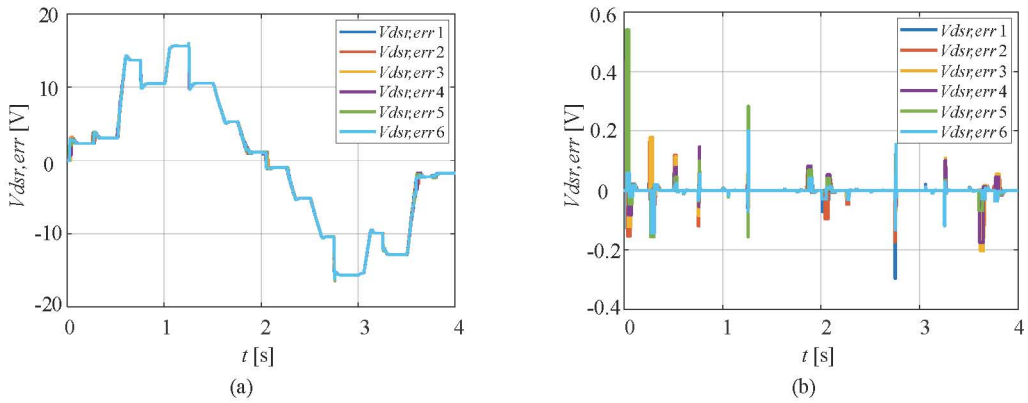

Fig. 3. (a) D-axis voltage errors during the operation with parameter errors and (b) their filtered values. $V_{dsr,errx}$ is the d-axis voltage error value which is measured at $\frac{\pi}{3}x$ rad electric angle.

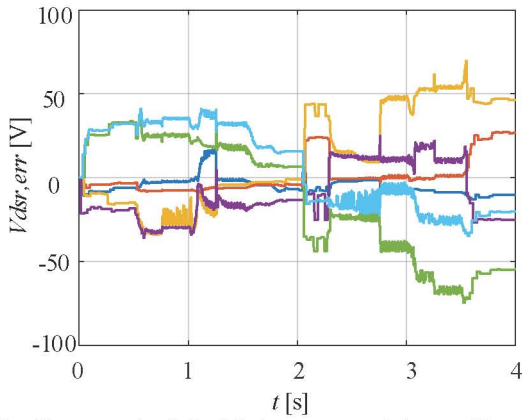

Fig. 4. $V_{dsr,err}$ under fault of A phase upper switch open. The color of each signal is the same with Fig. 3.

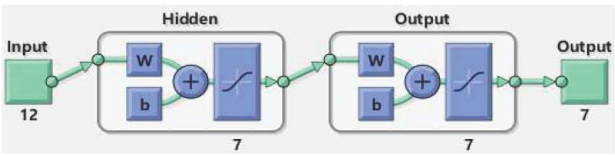

Fig. 5. Structure of the proposed ANN for the simulation.

parameters are investigated using FEA, the information can be utilized for obtaining better diagnosis performance in the real machine. The base speed of the machine and bandwidths of the system are shown in Table II. The training profile is also drawn in Fig. 2(a) as dotted red points and green arrows; the machine stays at each red point for 0.25 s. Fig. 2(b) shows the speed, torque, and currents according to the simulation time, and the machine was driven within MTPA operation. In Fig. 2, ω_{rm} and ω_r stands for mechanical and electric angular speed.

A dataset for each status was obtained for all the combinations of the 'known' values of L_{ds}, L_{qs} and R_s in the controllers among 1.1, 1.0 and 0.9 p.u.; so the machine operated along the profile in Fig. 2 for $27(= 3 \times 3 \times 3)$ times per each status. Fig. 3(a) shows the example waveform when L_{ds}, L_{qs} and R_s are known with the scales of 0.9, 1.1 and 1.1 p.u., respectively. If the operating point of a machine changes slowly, the voltage error terms generated due to the parameter errors become constant. So, in this paper, the voltage errors through a high-pass filter were sampled, where the bandwidth of the filters were 50 rad/s. Then, the voltage error waveform was obtained as Fig. 3(b).

Again, repeating the above step 7 times as changing the status of the machine (as Table I), the whole dataset was obtained. Each status can be emulated with a normal machine easily by nullifying one of the switching function. Fig. 4 shows the waveform of d-axis voltage error when upper switch on A phase is open, and the parameters are known correctly. The goal of the ANN is to distinguish such characteristic voltage error waveforms and to classify.

C. Setup and Training of ANN

Fig. 5 shows the shape of the proposing ANN. It is composed of 3 layers; an input layer, one hidden layer and the output layer with 12, 7 and 7 neurons. Bias inputs are also considered for the hidden and output layers. The configuration and training of the ANN were done using MATLAB® 'Statistics and Machine Learning Toolbox'. Output vector answers were given in Boolean form where each element indicates whether the machine is in the fault situation (in Table I) or not. For example, an output vector of [0 0 0 0 1 0 0] is given with twelve voltage error values, which are measured when the machine is operating under the fault of B phase upper switch open. For an input set, the estimated status is decided as the index of the output neuron with the largest value. For actuation function, hyperbolic tangent sigmoid function was selected for both hidden and output layers, and it is expressed as

$$x = \frac{2}{(1 + e^{-2y})} - 1 \tag{1}$$

where x is the output of the neuron, and y is the linear combination of the prior layer neurons and weights. Levenberg-Marquardt back-propagation (trainlm function in the toolbox) was applied for fitting the net to the dataset, and the ANN showed 99.8% of accuracy. The number of the hidden neurons was chosen by selecting the minimum

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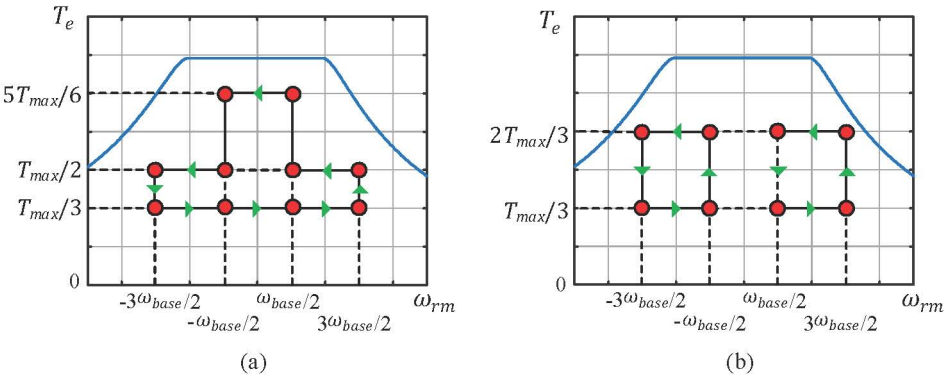

Fig. 6. Operation profiles for evaluating the ANN.

TABLE III
EVALUATION RESULT OF THE TRAINED ANN FOR PROFILE SHOWN IN FIG. 5(A) WITHOUT FAULT DIAGNOSIS GOVERNOR

Real status \ ANN output	1	2	3	4	5	6	7
1: Normal	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2: Fault – A phase upper switch open	0.0227	0.9708	0.0030	0.0015	0.0011	0.0000	0.0009
3: Fault – A phase lower switch open	0.0224	0.0023	0.9570	0.0004	0.0016	0.0003	0.0160
4: Fault – B phase upper switch open	0.0213	0.0026	0.0008	0.9725	0.0015	0.0001	0.0011
5: Fault – B phase lower switch open	0.0228	0.0005	0.0003	0.0006	0.9744	0.0011	0.0003
6: Fault – C phase upper switch open	0.0228	0.0010	0.0007	0.0014	0.0003	0.9729	0.0009
7: Fault – C phase lower switch open	0.0217	0.0013	0.0021	0.0007	0.0002	0.0015	0.9725

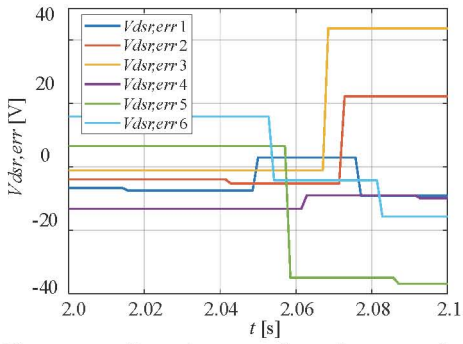

Fig. 7. $V_{dsr,err}$ waveform at zero speed crossing area under fault of A phase upper switch open.

number among the ones which make the accuracy larger than 99%.

III. EVALUATION OF ANN WITH SIMULATIONS

For testing the trained ANN, a new dataset obtained from the operation profiles shown in Fig. 6(a) and Fig. 6(b) are used, and it was repeated 27 times for each machine status with different combinations of L_{ds}, L_{qs} and R_s values. Note that all the staying points (red dots) in the profiles are not duplicated with the ones in Fig. 2(a). Table IV shows the classification results of the new dataset obtained with Fig. 6(a) profile. The green cells and orange cells in the Table III are 'true-positive' and 'false-positive' ratio, respectively, for each dataset (row). The average accuracy of the trained ANN for this test case was 97.4% which means that the error rate has highly increased.

The main reason for the low accuracy is found out to be zero-speed crossing. When the machine changes its rotating direction, it comes to operate in different function; motor and generator. In two cases, $V_{dqsr,err}$ waveforms of distinct characteristics are obtained as shown in Fig. 7, the zoomed view of Fig. 4 around $t = 2.1$ s. Since the ANN utilizes the voltage errors sampled through one electric cycle, the inputs of the ANN are then composed of signals of unexpected combination when the machine changes rotating direction. It is hard to train the ANN to cover this phenomena because the voltage error waveforms are highly dependent on the position of the machine at the zero-speed-crossing moment. For example, sometimes, an inverter with an open switch also can synthesize the required voltages with normal switches in it when the machine crosses the zero-speed or rotates slowly. Then the ANN would consider the system is not suffering from the switch open fault.

So, 'fault diagnosis governor' concept was proposed and implemented as Fig. 8 which decides when to utilize the ANN. The purpose of the governor is to utilize the ANN when the machine is operating above the threshold speed, 100 rad/s. In Fig. 8, a 'sector' stands for the area of $\pi/3$ electrical angle, so the diagnosis is done if the machine has rotated a whole electric cycle at least after getting faster than the threshold speed. With the proposed governor concept, the ANN gave no wrong answer all the time for the new dataset obtained with Fig. 6(a).

The trained ANN was tested again with two profiles shown in Fig. 6(b), separately. These new loops are generated not to include the zero-speed command. For both datasets of two new loops, the ANN always gave correct classification result, even without the aforementioned governor concept.

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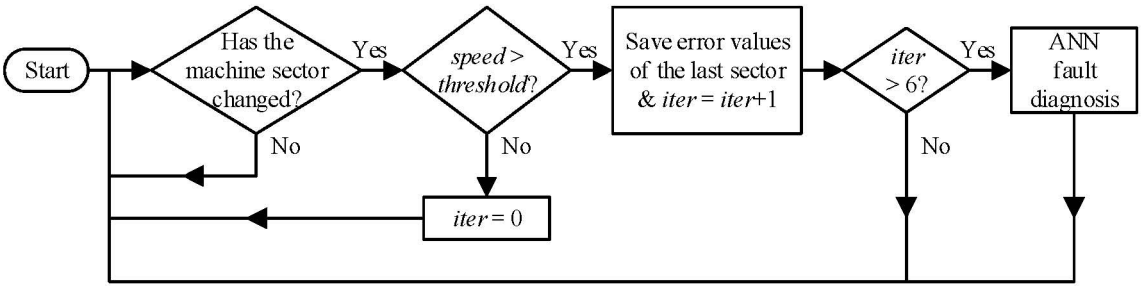

Fig. 8. Fault diagnosis governor concept for around-zero-speed area.

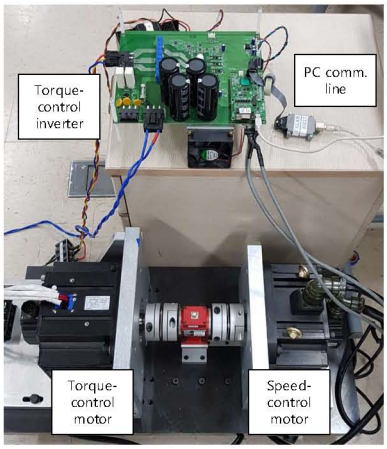

Fig. 9. Experiment set for performance verification of ANN fault diagnosing. The speed-control inverter is not shown in the figure. (Information from the torque sensor at the middle is not used.)

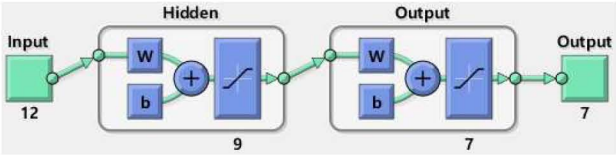

Fig. 10. Structure of the proposed ANN for the experiment. The number of hidden layer neurons and the activation functions are changed.

TABLE IV
NUMBER OF CALCULATION REQUIRED FOR FORWARD PROPAGATION

ANN model	Exponentiation	Division	Multiplication	Add/ Subtraction
<Simulation> 12-7-7 neuron, Tan-sigmoid	14	14	147	175
<Experiment> 12-9-7 neuron, Sat-linear	0	0	91	219

IV. EXPERIMENT – ONLINE FAULT CLASSIFICATION

The proposed concept was verified with an experiment. In the experiment, a normal machine controlled the speed and the target machine controlled the torque. Switch open faults are simulated on the torque-control motor by blocking the PWM signals to a specific switch. Fig. 9 shows the experiment test bed.

The training dataset in experiment was obtained with the profile shown in Fig. 2; datasets with parameter errors were also obtained. To reduce the calculation burden for the DSP, instead of tangent-sigmoid function, saturated linear function is applied as the activation functions for all neurons. The new activation function can be written as follow.

$$y(x) = \begin{cases} x, & |x| \le 1 \\ \mathrm{sign}(x), & |x| > 1 \end{cases} \tag{10}$$

Using the simplified activation function and the proposed fault diagnosis governor, the ANN required 9 neurons in the hidden layer for classifying all the training data correctly. Fig. 10 shows the fault diagnosing ANN for the experiment. After the training, weights and biases were copied into the DSP and only the forward propagation calculation was done on the DSP. Table IV shows the difference of required calculation in forward propagation of two ANN models. While the ANN used for diagnosing in experiment had larger number in adding/subtracting, it had smaller numbers in exponentiation, division and multiplication. For DSP, TMS320S28346 of TI was used and the switching frequencies for both motor were 10 kHz. For the ANN generated for the experiment, DSP took about 4 us to do the forward propagation calculation and to find out the largest probability among the outputs. As the interval of the double-sampling current controller was 50 us, the fault analysis process could be executed with no performance degradation in the motor control.

Using the trained ANN, the DSP could diagnose the status of the inverter correctly from the 12 voltage errors for all (red dotted) operation points in Fig. 2(a) and Fig. 6. Fig. 11 shows example online estimation results with voltage errors that are sent from DSP to PC; these are re-plotted with MATLAB®. From normal state, open faults of the A phase lower switch and C phase upper switch could be detected within one cycle. There were no wrong classification results before and after the fault.

V. CONCLUSION

An artificial neural network for switch open fault diagnosis is proposed. Inputs of the ANN are only twelve voltage errors of d- and q-axis with no post-processing, measured every $\pi/3$ electric angle. The outputs stand for probabilities of normal or 6 fault situations, so the DSP

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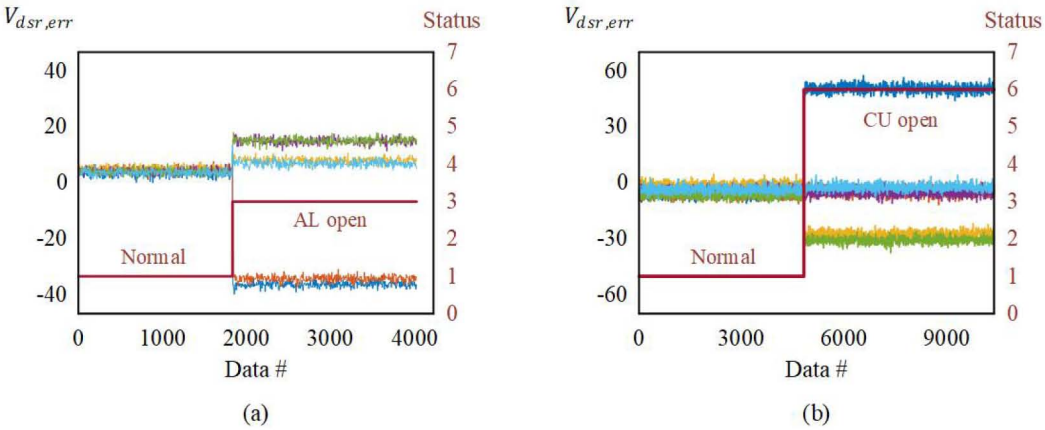

Fig. 11. Online fault diagnosis results on the DSP with voltage errors. Switch open fault detection of (a) A phase lower and (b) C phase upper switch.

concludes that the inverter is in the status with the largest probability. The training was done over wide operation area including field-weakening region while considering parameter errors. The trained ANN was tested in simulation and experiment with two operating profiles, and it could always give correct classification result.

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