

Fault diagnostics in power electronics-based brake-by-wire systems

M A Masrur^{1*}, H-J Wu², C Mi², Z-H Chen², and Y L Murphey²

¹ US Army RDECOM-TARDEC, Warren Michigan, USA

² Department of Electrical and Computer Engineering, University of Michigan-Dearborn, Dearborn, Michigan, USA

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Abstract: A d.c.-motor-based brake-by-wire system is studied for the purpose of fault diagnostics of the power electronic switches. The voltage and current generated in the switching circuit under normal and six faulted conditions are observed. A hierarchical fuzzy diagnostic system has been developed to detect certain types of fault condition in any specific solid state power switch at the moment immediately after the occurrence of the fault. The hierarchical fuzzy diagnostic system has been tested and validated using data from both a simulation and a laboratory set-up with a 1/3 hp d.c. motor and a d.c.-to-d.c. converter. The system performance has been compared with two different fuzzy diagnostic systems and the results are presented. The hierarchical fuzzy diagnostic system trained on the simulated model has the capability of detecting certain types of fault condition occurring in a brake-by-wire actuator system set-up in a laboratory in less than 0.0009 s and pinpointing the specific types of fault within less than 0.013 s.

Keywords: fuzzy logic, multi-class fault detection, brake-by-wire, power electronics, d.c. motor, d.c.-to-d.c. converter

1 INTRODUCTION

The automotive industry has given increased attention towards the replacement of mechanical and hydraulic systems in vehicles using either fully or partially electrical systems. In addition to the main propulsion, work has progressed towards the replacement of various auxiliary devices, which are currently operated using mechanical, hydraulic, or pneumatic methods. These devices include steering, brakes, suspension, and various mechanical pumps. The mechanical systems are relatively heavy and difficult to package. On the other hand, electrical systems are easier to package since the wiring is flexible. Electrical systems use motors and solenoids as actuators and have a fast response. However, if the motor system fails, the entire electrical system related to the motor ceases to function properly. A

motor system consists of a battery, wiring, power electronics, an embedded controller, and the motor itself.

This paper presents the research on fault diagnostics in brake-by-wire actuator systems. Brake-by-wire systems and other X-by-wire systems with fully electromechanical devices or partial mechanical backup systems have been studied by various researchers [1–12]. Some of these studies discussed have the behaviour of the brake in the context of the whole vehicle and how the brake system behaviour influences the overall vehicle performance. Others have discussed electrohydraulic systems including slip control, precise computation of the brake force, and traction control. However, in the literature, research work on fault diagnostics in the motor and its controller in brake-by-wire systems has not been reported in depth. Fault diagnostics technology for internal combustion engine vehicles has been well investigated [13–15], but much less so in electrical system diagnostics. Moseler and Isermann [12] described a black-box-type model using a polynomial differential-algebraic equation with

*Corresponding author: Mobility Technology, US Army RDECOM-TARDEC, AMSRD-TAR-R, MS-264, 6501 East 11 Mile Road, Warren, Michigan, 48397-5000, USA. email: md.abul.masrur@us.army.mil

application to a brushless d.c. machine. There these workers estimated system parameters under normal and faulted conditions and compared the same with the current system parameter values; if any discrepancy with the normal condition was seen, a faulty condition was declared. However, the parameter-estimated model can easily lose the intuitive focus of the system and in general cannot point towards the specific problem and its location. In addition, the model can encounter a topological change after a fault, and hence the premises on which the model was originally developed and the parameters estimated may not hold any longer.

This paper is focused on the diagnostics of power electronics switches since they are often considered to be the weakest link in the brake-by-wire system, i.e. in the whole link from the brake pedal to the brake shoe actuator. The objective is to locate accurately any faults within the power electronics of a brake-by-wire system as soon as they occur. A brake-by-wire actuator system model was developed using Simplorer software that implements the full control of the power electronics switches and emulates six different fault conditions. A test bench was designed for the actuator system. The simulated model and the bench tests are compared under normal and fault conditions. A hierarchical fuzzy diagnostic system has been developed and trained to detect all specified fault conditions in the actuator system. The hierarchical fuzzy diagnostic system is designed on the basis of the structure of the brake-by-wire actuator system. It has the capabilities of detecting fault conditions almost immediately after they occur and pinpointing specific fault conditions within less than 0.02 s on the bench set-up. The performance of the hierarchical fuzzy diagnostic system is also compared with two other fuzzy diagnostic systems, and the results are presented in the paper.

2 A THEORETICAL MODEL OF THE BRAKE-BY-WIRE ACTUATOR SYSTEM

Figure 1 illustrates a quarter-model of the system architecture of a fully electro-mechanical brake-by-wire system. Although many types of motor can be used for the brake-by-wire system, a brushed d.c. motor is selected because it is inexpensive and is available in the automotive industry abundantly. The characteristics of a brushless motor, for example, can be represented using equations similar to a brushed d.c. motor, and the failure mechanisms are very similar to each other. Furthermore, in the configuration described, the power electronics system can be implemented using a four-switch bridge, unlike the six-switch bridge for a three-phase system. This factor also adds to the cost benefit, which is one of the most important concerns in the automotive industry. The brushed d.c. motor in this study either can be permanent magnet-based or can have a field winding. The system has four actuator motors corresponding to each wheel. The position signal from the brake pedal is fed to a controller which generates a control signal to activate one or more of the four brake motors. Each motor may have a separate control wire from the controller to allow the four actuators to run independently, which is more robust during a failure of one or more of the actuators. Each motor has its own power electronics converter which receives control command from the main controller and controls each motor separately. This helps to increase the robustness during a failure of one or more of the actuators as the remaining actuators will still function.

The simulation model for the brake-by-wire system is illustrated in Fig. 1(a). The block diagram of the simulated system is shown in Fig. 1(b). The input to the system is the pedal position and pedal speed, which are transformed to T_{ref} , the reference torque.

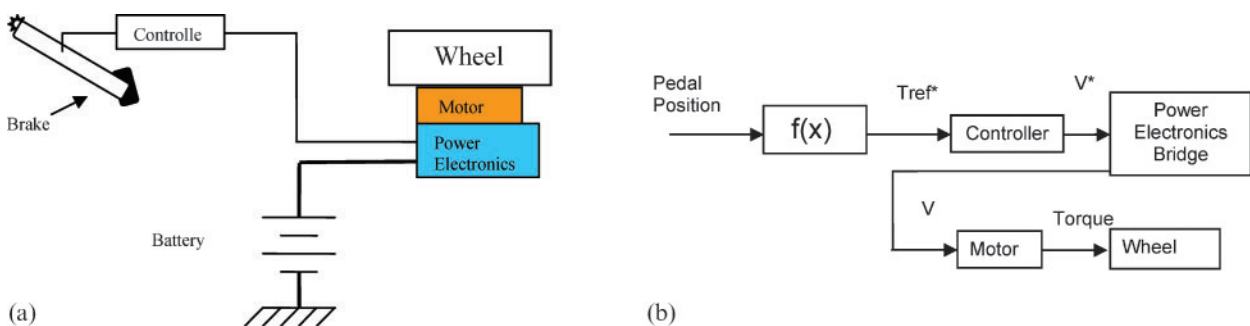


Fig. 1 Brake-by-wire system: (a) architecture of a brake-by-wire system; (b) the system diagram for a brake-by-wire system

The electromechanical system can be described through the equations

$$V_a = R_a I_a + L_a \frac{dI_a}{dt} + K \Phi \omega \quad (1)$$

$$T = K \Phi I_a \quad (2)$$

$$T = J \frac{d\omega}{dt} + B\omega + T_L \quad (3)$$

where V_a is the armature voltage, I_a is the armature current, R_a is the armature resistance, L_a is the armature leakage inductance, K is the motor constant, Φ is the total flux per pole, ω is the angular speed of the motor, T is the output torque of the motor, J is the inertia of the actuator system which includes the motor rotor, and the loads connected to the driving shaft, B is the damping, and T_L is the load torque (braking force).

The motor voltage can be derived from the brake pedal position and pedal force. If the pedal force (or corresponding torque) is T_{ref} , then it can be shown that the required motor voltage in Fig. 1(b) is given by

$$V_a^* = R_a \frac{T_{ref}}{K \Phi} + \frac{L_a}{K \Phi} \frac{dT_{ref}}{dt} + K \Phi \omega \quad (4)$$

The power electronics circuit to actuate the motor is illustrated in Fig. 2. Based on equation (4), a reference voltage is obtained from the d.c. battery through pulse width modulation (PWM) techniques. In Fig. 2, the motor voltage is

$$V_a^* = (2D - 1)V_B \quad (5)$$

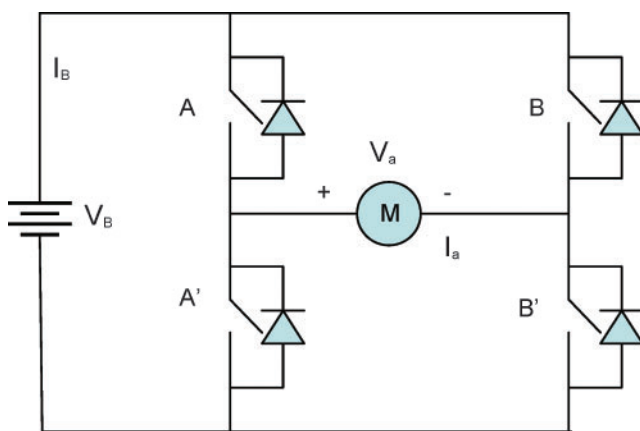


Fig. 2 The inverter circuit diagram for the brake-by-wire system

where D is the switching duty ratio of switch A and V_B is the battery voltage.

3 SIMULATION STUDIES OF FAULTY CONDITIONS OF BRAKE-BY-WIRE SYSTEMS

The system model shown in Fig. 1(b) is implemented by using Simplerer-based simulation which can simulate various fault conditions of the four-switch scheme shown in Fig. 2. Figure 3 shows the simulated current and voltage waveforms under normal and different faulty conditions. The ratings and parameters of the test motor are shown in Table 1. It should be noted that the particular motor used was a higher-voltage motor, rather than a motor that would normally be encountered in an automotive environment. This is due to the limitation of available resources. Nevertheless, the principles are well illustrated. In these simulations, the duty ratio of switch A is set to 70 per cent.

It is worth noting that, at 70 per cent duty ratio, the open-circuit fault caused by a broken switch in B and/or A' cannot be detected, which can be explained by following the current paths through the switches and the diodes. In order to detect the open-circuit fault condition caused by B and A', a duty ratio of less than 50 per cent must be applied. In other words, as soon as a duty ratio of less than 50 per cent is applied, the fault signal can be captured.

It is also worth pointing out that the fault conditions have symmetrical characteristics due to the symmetry of the power electronics circuit. For example, in Fig. 2, switch A with an open-circuit fault will result in the same behaviour as B' with an open-circuit fault; similarly, B with an open-circuit fault will result in the same behaviour as A' with an open-circuit fault. In summary, at any given time, one of the six fault classes can occur in the circuit shown in Fig. 2. They are denoted hereafter as follows: A or B' open; A' or B open; AA' or BB' open; A or B' short; A' or B short; AA' or BB' short.

A bench set-up was implemented consisting of a permanent magnet-brushed d.c. motor, a full bridge converter, and a dSPACE controller as shown in Fig. 4. The bench set-up system has the capabilities to generate current and voltage signals under normal operating conditions as well as various fault conditions. The signals generated by the bench set-up and the simulation model have similar behaviours. In the bench set-up, the d.c. motor serves as the brake-by-wire actuator, and the a.c. motor serves as the brake and is programmed to emulate a car brake system.

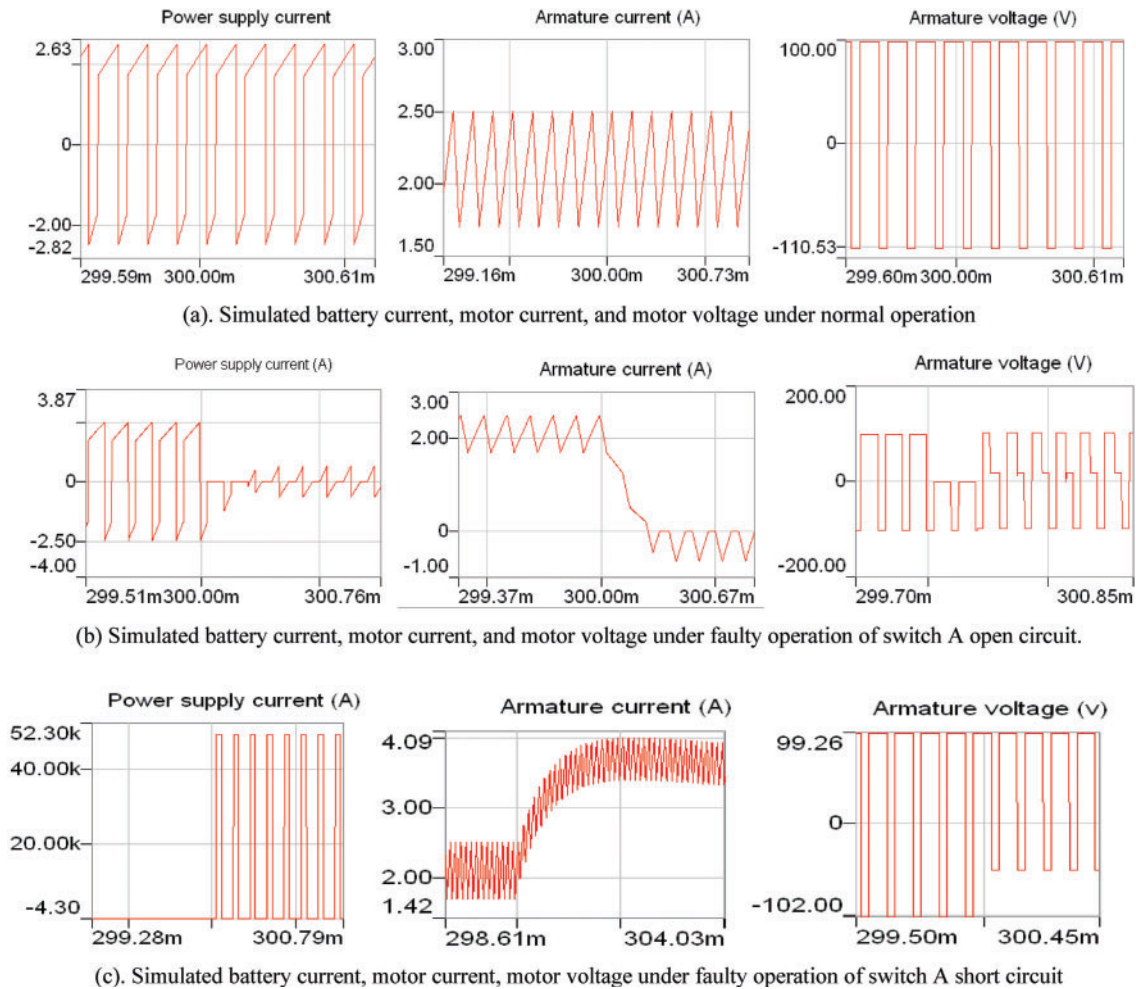


Fig. 3 Simulated voltage and current waveforms under normal and fault conditions

For the laboratory set-up experiments, the open-circuit faults were emulated by simulating any one or more of the switches open. The parameters (Table 1) of the motor tested are the same as those used in the simulation. The faults being tested include the following: A or B' open; B or A' open; both A and B' open; both B and A' open. Figure 5 gives an example of the signals generated by the simulation program and the laboratory set-up test when the circuit has a fault caused by switch A open

Table 1 Parameters of the motor used in the simulation and experiment set-up

Rated voltage	125 V
Rated current	3.2 A
Rated power	1/3 hp
Rated speed	1800 r/min
Armature resistance R_a	8.98 Ω
Armature leakage inductance	5.35 mH
Machine constant $K\Phi$	0.45 V s/rad
Inertia	0.6×10^{-3} kg m ²

circuit. In the experiments, the sampling of data has a limited rate. Therefore, only the average is sampled whereas, in the simulation, the data can be sampled at a very high rate to show the detailed switching behaviour. For ease of comparison, the simulation data have to be processed. For this comparison, the simulated data were processed using a 1000-point moving average. It can be seen that the test data match the simulation very well.

4 A HIERARCHICAL FUZZY DIAGNOSTIC SYSTEM FOR FAULT DETECTION IN A BRAKE-BY-WIRE SYSTEM

As was shown in the previous section, the fault conditions are manifest in three output signals, i.e. motor current, power supply current, and motor voltages, denoted as I_{mot} , I_{bat} , and V_{mot} respectively.

Fault diagnostics in the brake-by-wire system are performed by an intelligent system that has the

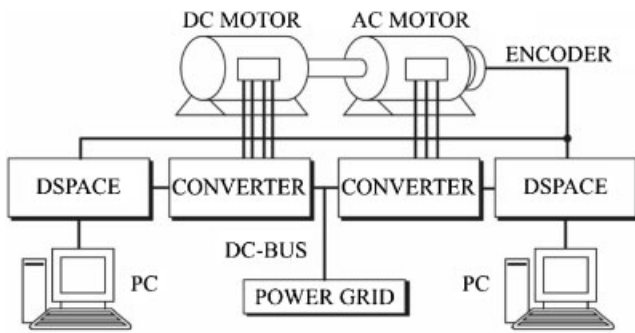


Fig. 4 Schematic diagram of the test bench set-up

capability of detecting six different classes of fault as soon as they occur. Figure 6 illustrates the major computational blocks involved in the proposed fuzzy brake-by-wire fault diagnostic system, which consists of two stages: offline training and online diagnostics. During the training stage, a set of training data is generated by a simulation programme, a laboratory set-up, or physical data from a brake-by-wire device. The training dataset should contain three signals, $I_{mot}^i[t_0, t_e]$, $I_{bat}^i[t_0, t_e]$, $V_{mot}^i[t_0, t_e]$, generated under the scenario of i th fault condition, for $i = 1, \dots, k$, where k is the number of fault conditions to be detected. The time interval $[t_0, t_e]$ represents the simulation time used to generate the signals.

Based on the brake-by-wire system presented in Fig. 1 and the simulation model described in section

3, a fault diagnostic system has been designed to detect the following six fault classes as soon as they occur in the system.

- Class 1. Switch A or switch B' is open.
- Class 2. Switch B or switch A' is open.
- Class 3. Both switch A and switch A' are open.
- Class 4. Switch A or switch B' is short.
- Class 5. Switch A' or switch B is short.
- Class 6. Both switch A and switch A' are short circuited or both switch B and switch B' are short.

The first computational step is to segment the signals of the i th fault class into a set of segments, S_I^i , and to extract the signal features from each segment in S_I^i , for $i = 1, \dots, k$. All feature vectors extracted from signal segments form a training data set which is used by a fuzzy learning algorithm to generate a fuzzy knowledge base that consists of fuzzy rules and fuzzy membership functions. At the online diagnostic stage, at any given time t , the condition of the brake-by-wire system is detected on the basis of the behaviours of the three signals, $I_{mot}[t-\Delta t, t]$, $I_{bat}[t-\Delta t, t]$, $V_{mot}[t-\Delta t, t]$ within the time interval $[t-\Delta t, t]$. The feature vectors are extracted from these three signal segments and the results are sent to the fuzzy brake-by-wire diagnostic system, which in turn determines whether the system is under the normal operation condition, or under one of the six fault conditions. The following two sections 4.1 and 4.2 describe the two

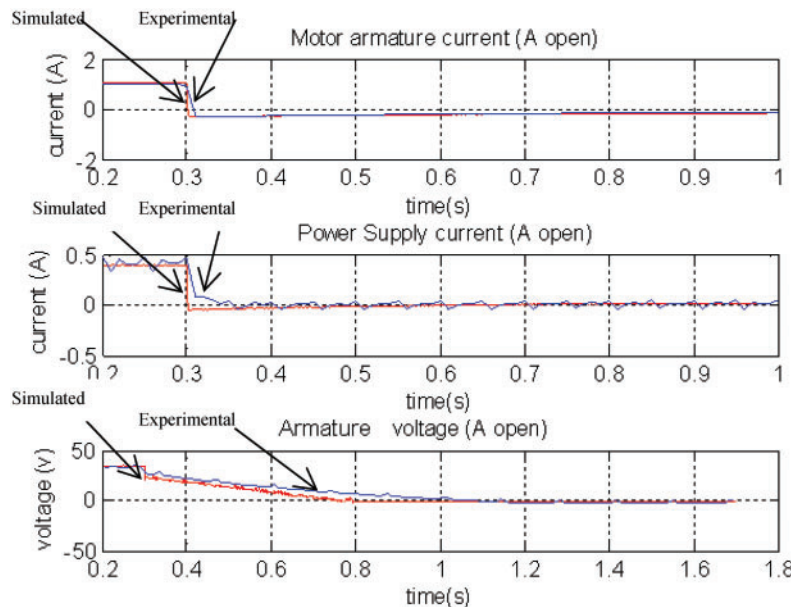


Fig. 5 Comparison of the simulated and experimental motor currents, power supply currents, and motor voltages in a fault condition (switch A open). The relatively smooth curves with sharp step changes in command can be noted in the simulated results

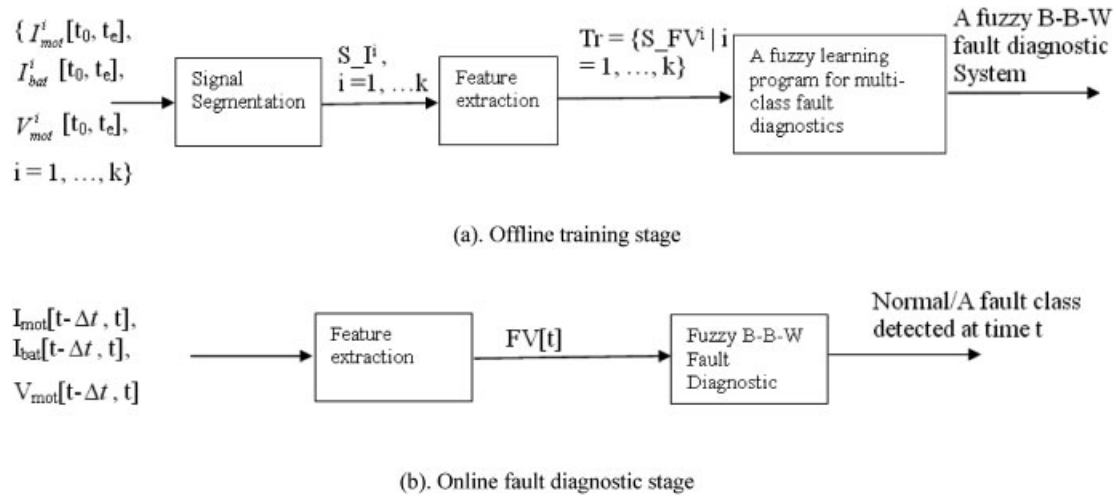


Fig. 6 Computational steps in a fuzzy brake-by-wire (B-B-W) fault diagnostic system: (a) offline training stage; (b) online fault diagnostic stage

major computational components in the fuzzy brake-by-wire fault diagnostic system, signal segmentation and feature selection, and a hierarchical fuzzy multi-class diagnostic system.

4.1 Signal segmentation and feature extraction

Under each fault condition i , the three signals $I_{mot}^i[0, t_e]$, $I_{bat}^i[0, t_e]$, and $V_{mot}^i[0, t_e]$, $i = 1, \dots, 6$, are first segmented into three sequences of segment denoted as $S_{-I_{mot}^i}$, $S_{-I_{bat}^i}$, and $S_{-V_{mot}^i}$, where

$$S_{-I_{mot}^i} = \{S_{-I_{mot}^i}[(j-1)\Delta t, j\Delta t] | j=1, \dots, n, \text{ and } n\Delta t = t_e\} \quad (6)$$

$$S_{-I_{bat}^i} = \{S_{-I_{bat}^i}[(j-1)\Delta t, j\Delta t] | j=1, \dots, n, \text{ and } n\Delta t = t_e\} \quad (7)$$

$$S_{-V_{mot}^i} = \{S_{-V_{mot}^i}[(j-1)\Delta t, j\Delta t] | j=1, \dots, n, \text{ and } n\Delta t = t_e\} \quad (8)$$

S_{-I^i} denote all the segments generated from $I_{mot}^i[0, t_e]$, $I_{bat}^i[0, t_e]$, and $V_{mot}^i[0, t_e]$, i.e. $S_{-I^i} = \{S_{-I_{mot}^i}, S_{-I_{bat}^i}, S_{-V_{mot}^i}\}$.

Since the three signals are acquired simultaneously, they are segmented into three sequences that consist of the same number of fixed sized segments. In every sequence, the two adjacent segments are overlapped by one third of each segment in order to maintain continuity of information flow between segments. The details of the segmentation scheme are omitted here for brevity. Each segment is represented by three features: minimum, maximum, and average values within the segment. At time interval $[(j-1)\Delta t, j\Delta t]$, a feature vector is defined as

$$FV_j^i = \langle \min_{-}\alpha_j^i, \max_{-}\alpha_j^i, \text{ave}_{-}\alpha_j^i, \min_{-}\beta_j^i, \max_{-}\beta_j^i, \text{ave}_{-}\beta_j^i, \min_{-}V_j^i, \max_{-}V_j^i, \text{ave}_{-}V_j^i \rangle$$

where α_j^i , β_j^i , and V_j^i are the j th segments of I_{mot}^i , I_{bat}^i , and V_{mot}^i respectively, generated by simulating the i th fault class. The output from the feature extraction block at the training stage is a set of feature vectors FV^i defined as follows: $FV^i = \{FV_j^i | j=1, \dots, n\}$. The training data used by the fuzzy learning program contain all the feature vectors in FV^i for all $i = 1, \dots, k$.

At the online diagnostic stage, fault detection is based on the three signals acquired within the time interval $[t-\Delta t, t]$. From the three signal segments $I_{mot}[t-\Delta t, t]$, $I_{bat}[t-\Delta t, t]$, and $V_{mot}[t-\Delta t, t]$, a feature vector $FV[t]$ is extracted, where

$$FV[t] = \{\min_{-}\alpha(t), \max_{-}\alpha(t), \text{ave}_{-}\alpha(t), \min_{-}\beta(t), \max_{-}\beta(t), \text{ave}_{-}\beta(t), \min_{-}V(t), \max_{-}V(t), \text{ave}_{-}V(t)\}$$

The fuzzy brake-by-wire fault diagnostic system will use the fuzzy knowledge bases generated at the training stage to derive the diagnostic decision, with the brake-by-wire system in the normal condition or one of the six faulty conditions.

4.2 A hierarchical fuzzy diagnostic system for brake-by-wire fault detection

Fuzzy logic has been popular in engineering fault diagnostics [16–20]. However, there has not been

much discussion in the literature on different fuzzy system architectures for multi-class fault detection. There are a number of approaches that can be used to model a fuzzy multi-class classification problem. This paper presented a hierarchical fuzzy diagnostic system F designed on the basis of the brake-by-wire system structure. Figure 7 illustrates the diagnostic stage of F . F has six fault diagnostic systems F^i for $i = 1, 2, \dots, 6$. F^1 is designed to detect normal conditions from abnormal conditions. When F^1 decides that the current condition of the brake-by-wire system is normal, F immediately exits to process the next signal segment. Since most of the time a brake-by-wire system is in the normal condition, this system architecture ensures fast detection. When F^1 detects an abnormal condition, it activates F^2 , which is designed to detect whether the brake-by-wire system is in the short-circuit or open-circuit condition. If it is in the short-circuit condition, then F^3 is activated, which decides whether the brake-by-wire system is single-switch or double-switch short circuited. If it is single-switch short circuited, F^5 is called to find out whether A or B' is short circuited, or whether A' or B is short circuited. If F^2 decides that the brake-by-wire system is in an open-circuit fault, F^4 is called to find out whether the brake-by-wire system is single-switch or double-switch open circuited. If it is single-switch open circuited, F^6 is called to find out whether A or B' is open circuited, or A' or B is open circuited.

Fuzzy reasoning is performed within the context of a fuzzy system model, which consists of the control, the

solution variables, the fuzzy sets, the proposition (rule) statements, and the underlying control mechanisms that tie all these together into a cohesive reasoning environment. All six fuzzy diagnostic systems in F share the same input space, a nine-dimensional feature space as described in the last section. Therefore each fuzzy system has nine control variables $FV = \{I_{mot}^{min}, I_{mot}^{max}, I_{mot}^{ave}, I_{bat}^{min}, I_{bat}^{max}, I_{bat}^{ave}, V_{mot}^{min}, V_{mot}^{max}, V_{mot}^{ave}\}$ and one solution variable y to indicate whether the input vector FV is likely to be in class 0 or class 1. The fuzzy learning algorithm presented in reference [20] is used to generate a fuzzy knowledge base for each fuzzy system based on the data generated by the simulation model presented in the last section.

5 EXPERIMENTS AND SYSTEM EVALUATION

The simulation model described in the last section was used to generate training and testing data. The simulation system has the following simulation parameters: d.c. motor with $V_{d.c.} = 100$ V, $R_a = 8.98 \Omega$, $L_a = 0.00535$ H, initial speed of $(650/60) \times 2 \times \pi$ rad/s, and a frictional torque of 0.1 N m. The inverter's parameters were set to a PWM frequency of 5 kHz. Three signals, namely the battery current I_{bat} , the motor current I_{mot} , and the motor voltage V_{mot} , are measured for all six fault classes presented above. Each fault event was triggered at the end of the first second, and the entire simulation takes 2 s.

The training data are collected and segmented as follows. For every fault class, the fault part of the

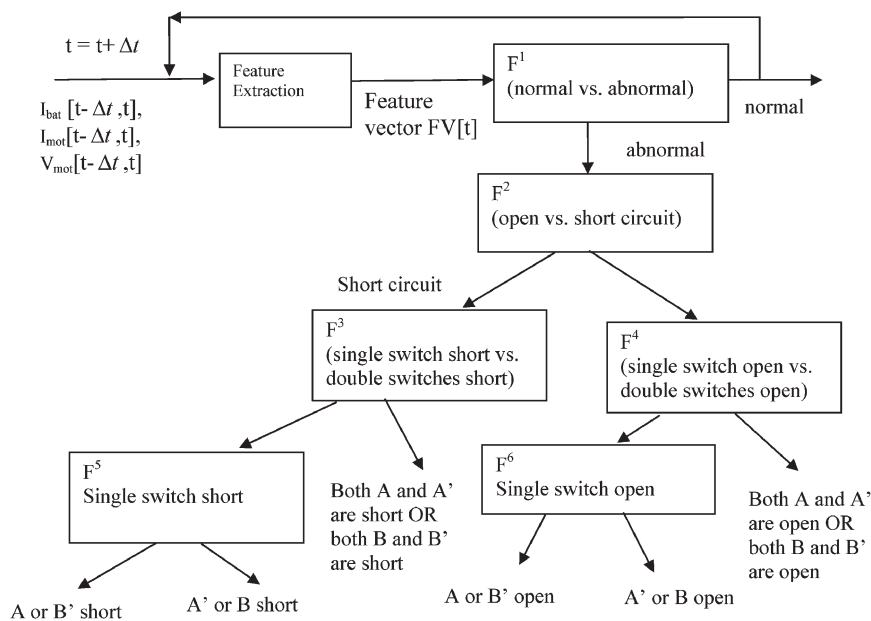


Fig. 7 A hierarchical fuzzy diagnostic system for fault detection in a brake-by-wire system

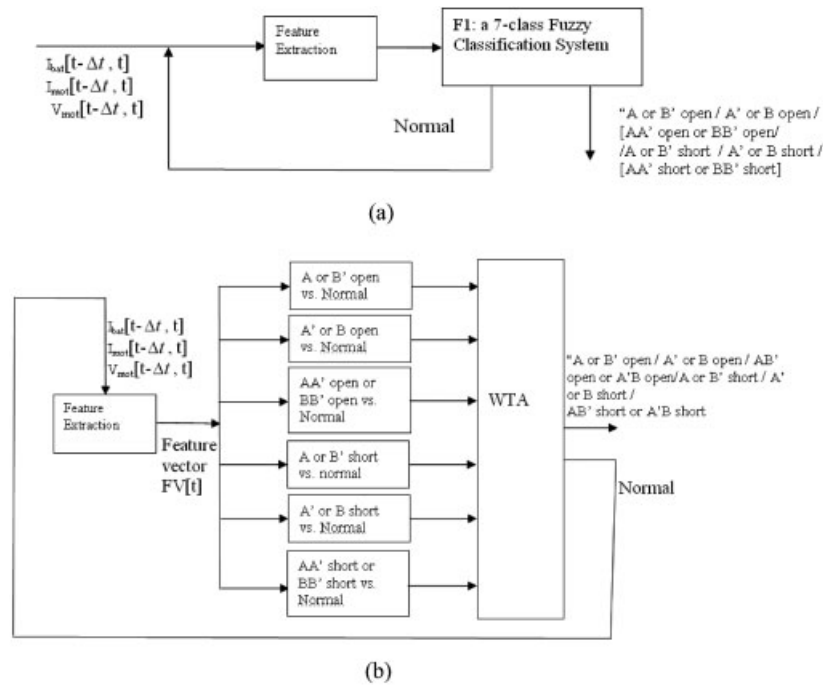


Fig. 8 Two fuzzy diagnostic systems: (a) a single seven-class fuzzy fault classification system; (b) a fuzzy diagnostic system modelled using a fault-against-normal scheme

signals has a duration of 15 ms, i.e. 15 000 data samples were generated at a 1 μ s sampling rate. All three signals I_{mot} , I_{bat} , and V_{mot} for each fault class, are segmented simultaneously into segments of 60 samples in each, with an overlap of 20 samples between two adjacent segments. The fault portion of the signals was segmented into 378 segments.

A feature vector is extracted from three signal segments I_{mot} , I_{bat} , and V_{mot} that occur at the same time interval as described in the last section. All those feature vectors are divided into seven datasets, C_0, C_1, \dots, C_6 , where C_0 contains the feature vectors extracted from the normal signal segments, and C_1, \dots, C_6 contain the feature vectors representing the respective fault classes. Each C_i is divided randomly into a training and a test set in a ratio of 2:1.

For the purpose of evaluating the structured hierarchical fuzzy diagnostic system, two additional fuzzy diagnostic systems were developed to model with a fault-against-normal scheme. Figures 8(a) and (b) illustrate the architectures of these two systems. The single seven-class fuzzy classification system has the same nine control variables as the structured fuzzy diagnostic system, and it has one output variable that has seven terms representing the normal class and the six fault classes.

The fuzzy diagnostic system shown in Fig. 8(b) is a set of six independently trained fuzzy diagnostic systems, each of which was trained by one fault class

against the normal class. The decision module, winner takes all (WTA), selects the output class that has the highest fuzzy belief value.

Tables 2 to 5 show the performances of these three fuzzy diagnostic systems on the test dataset. Table 2 shows that the single fuzzy system (see Fig. 8(a)) for the seven-class fault diagnostic system completely missed the fault class A' or B open. Table 3 lists the detailed performances of the six individual fuzzy diagnostic systems used in the fault versus normal scheme (see Fig. 8(b)), and Table 4 lists the entire system performance after a WTA scheme (see Fig. 8(b)) is applied to the outputs from the six fuzzy diagnostic systems. The fault class A or B' open has a rather low detection rate. The performances of all the six fuzzy diagnostic systems in the hierarchical fuzzy diagnostic system illustrated in Fig. 7 are listed in Table 5. All six individual fuzzy diagnostic systems

Table 2 Diagnostic performances of the single fuzzy classification system illustrated in Fig. 8(a)

Case	Correct rate
Normal	100
A or B' open	96.78
A' or B open	0
AA' or BB' open	100
A or B' short	100
A' or B short	100
AA' or BB' short	100
Total	84.27

Table 3 The performances of six fuzzy diagnostics modelled using the fault versus normal scheme in the system illustrated in Fig. 8(b)

Fault type	Normal class correct rate (%)	Fault class correct rate (%)	Overall correct rate (%)
F^1 : normal versus A or B' open	100	100	100
F^2 : normal versus A' or B open	100	100	100
F^3 : normal versus AA' or BB' open	100	98.51	99.21
F^4 : normal versus A or B' short	100	95.07	97.22
F^5 : normal versus A' or B short	100	100	100
F^6 : normal versus AA' or BB' short	100	100	100

Table 4 The system performance of the fuzzy fault versus normal combined with a WTA decision (see Fig. 8(b))

Case	Correct rate (%)
Normal	100
A or B' open	85.48
A' or B open	100
AA' or BB' open	95.52
A or B' short	95.07
A' or B short	100
AA' or BB' short	100
Total	96.44

performed well. Table 6 lists the performance of the hierarchical fuzzy diagnostic system (see Fig. 7) on all classes. It gave 100 per cent detection on the normal class and three fault classes, and more than 99 per cent on the other three fault classes.

In order to evaluate the robustness of the proposed diagnostic method, a set of experiments was conducted using the data acquired through the laboratory test set-up described in the last section. Because of the sampling rate limitation of the data acquisition system, the data were sampled at about every 10 ms and only three fault classes were generated: class 1, A or B' open; class 2, A' or B open; class 3, AA' or BB' open. The three fuzzy systems are as follows: F^1 is trained to detect normal versus abnormal; F^2 is trained to identify whether the current fault is {A or B' open, A' or B open} or AA' or BB' open; F^3 is trained to identify whether the current fault is {A or B'} open, or {A' or B} open. All

three systems are trained on simulation data and tested on the laboratory-generated data.

Since the motor voltage signal from laboratory data is asynchronous and has a sampling rate that is different from the motor current and the battery current, the three signals cannot be mixed in system training. Therefore only the battery current I_{bat} and the motor current I_{mot} are used in the system test on the laboratory data.

When the hierarchy fuzzy diagnostic system, which is trained on the simulation data described earlier, is tested on the laboratory-generated data, it detected 100 per cent correctly for normal conditions and 100 per cent correctly for fault conditions as soon as they occurred. However, the identification of the type of fault condition took a few segments after the fault condition occurred. Class 1, A or B' open, was identified correctly at the fifth segment after the fault condition occurred; class 2, A' or B open, was identified immediately as a class 2 fault as soon as it occurred; class 3, AA' or BB' open, was identified correctly at the fourteenth segment after the fault condition occurred. The hierarchical fuzzy diagnostic system takes about 0.0009 s to make a diagnostic decision for a given signal segment on a personal computer (PC) with the Windows XP system and a PM 1.73 processor. Any abnormal conditions are detected within 0.0009 s after they occur. For the fault class identity, class 2 is immediately identified, which takes 0.0009 s; class 1 is identified in 0.0045 s, and class 2 is identified in

Table 5 The performances of the six fuzzy diagnostics used in the hierarchical fault diagnostic system illustrated in Fig. 7

Fault type	Class 0 correct rate (%)	Class 1 correct rate (%)	Overall correct rate (%)
F^1 : class 0: normal versus class 1 abnormal	100	100	100
F^2 : class 0: open versus class 1: short	100	100	100
F^3 : class 0: single-switch short versus class 1: double-switch short	100	98.51	99.21
F^4 : class 0: single-switch open versus class 1: double-switch open	99.25	99.25	99.25
F^5 : class 0: A or B' short versus class 1: A' or B short	100	100	100
F^6 : class 0: A or B' short versus class 1: A' or B short	100	99.30	100

Table 6 Overall performance of the hierarchical fuzzy fault diagnostic system illustrated in Fig. 7

Case	Correct rate (%)
Normal	100
A or B' open	99.19
A' or B open	99.30
AA' or BB' open	99.25
A or B' short	100
A' or B short	100
AA' or BB' short	100
Total	99.68

0.0126 s. The detection time was measured according to the time needed to detect the faults after they occurred by the proposed hierarchical fuzzy diagnostic system running on a PC with the Windows XP system and PM 1.73 processor.

These results show that the proposed hierarchical fuzzy diagnostic system trained on the basis of a simulated brake-by-wire model has the capability of correctly identifying all fault conditions in real time over a wide operating domain.

6 DISCUSSION AND CONCLUSIONS

This paper presented an analytical model of the brake-by-wire system using an electromechanical actuator and implemented a simulation of the same using the Simplorer software by Ansoft. A bench set-up was also developed for the brake-by-wire system. A d.c. motor was used as an actuator, since it is more abundantly available with the present automotive supplier base. A very simple system was used, since cost-effectiveness is of prime concern in the automotive industry. However, the methodology illustrated is easily extendable to other kinds of motor and the principles discussed here still remain valid. Both the simulated and the bench test systems have the capabilities of generating current and voltage signals under normal operating conditions and fault conditions. An innovative hierarchical fuzzy diagnostic system has been developed on the basis of the structure of a brake-by-wire system to perform fault diagnostics. The hierarchical fuzzy diagnostic system gives 99.68 per cent classification accuracy on all signal segments generated by the simulation model. While tested on the data generated by the brake-by-wire system in a bench set-up, the hierarchical fuzzy diagnostic system has the capability of detecting any of the specified fault conditions in less than 0.0009 s and pinpointing to the specific types of fault within less than 0.013 s. This indicates that the proposed hierarchical

fuzzy diagnostic system has the promise of being implemented easily in a real-time environment in the automobile and operating robustly in a wide range of conditions. Although a brake-by-wire system was used with application in the automotive environment in mind, the methodology is equally applicable to other systems where such motors are used, including manufacturing and other non-mobile platforms. These will be studied and reported by the present authors in future work.

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