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Fault Detection via Stability Analysis for the Hybrid Control Unit of HEVs

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***Abstract*—**Fault detection determines faultexistence and detecting time. This paper discusses two layered fault detection methods to enhance the reliability and safety. Two layered fault detection methods consist of fault detection methods of component level controllers and system level controllers. Component level controllers detect faults by using limit checking, model-based detection, and data-driven detection and system level controllers execute detection by stability analysis which can detect unknown changes. System level controllers compare detection results via stability with fault signals from lower level controllers. This paper addresses fault detection methods via stability and suggests fault detection criteria in nonlinear systems. The fault detection method applies tothe hybrid control unit of a military hybrid electric vehicleso that the hybrid control unit can detect faults of the traction motor.

***Keywords*—**Two Layered Fault Detection, Stability Analysis, Fault-Tolerant Control

I. Introduction

A fault is an unpermitted deviation with abrupt, incipient or intermittent patterns. The fault can cause a failure which is a permanent interruption and leads unstable states of the system. It is highly related to reliability, availability, maintainability, and safety and has been analyzed based on experimental data or operation variables to improve reliability, availability, maintainability, and safety. FMEA (Failure Mode and Effects Analysis) and FTA (Fault Tree Analysis) are useful procedures to analyze each potential failure mode in a product to determinetheeffects, its criticality, and cause[1]. Large amounts of experimental data about failure modes have been mainly providedformilitary applications.

However, new patterns of faults have been generated, as electric/electronic/software systems have been steeply become popular and their controllability has been delicately improved. As a result, interest infault detection and diagnosis (FDD) has been growing in monitoringthe ongoing faults and in system degradation. Precise fault detection becomes more and more critical to ensure system stability.

Yang, Jiang, and Cocquempont (2010) addresses the combination of general fault detection and energy-based fault detection. The novel energy based on fault detection technique is concerned with the energy analysis related to dissipativity. They suggest stable switching strategies in hybrid systems.

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Isermann(2006) discussescomparison of each fault detection methods and combination of different fault-detection methods. Depending on applications, different fault detection methods can be selected for better detection performance. Proper combination of different fault-detection makes use of their advantages and generates relevant analytical symptoms for integrated FDD.

Kim, Song and Song (2009) presents two layered FDD using decentralized and centralized schemes. Two layered fault detection improves detection capability of faults. They applied the two layered FDD scheme to an ATV to prove advantages of robustness and accuracy of fault detection.

This paper presents fault detection methods via stability analysis for the HCU (Hybrid Electric Vehicle) of a HEV. In Section 2, fault models and two layered fault detection are presented. Fault detection methods via stability of the HCUare discussed in Section 3. Section 4 proposes an example of application. A conclusion is made in Section 5.

II. Fault Models and Two Layered Fault Detection in Nonlinear Systems

A. Fault Models in Nonlinear Systems

Consider the general nonlinear system

$$\dot{x} = f(x) + g(x)u \qquad (1)$$
$$y = h(x)$$

where $x \in \Re^n$ is the state, $u \in \Re^m$ is the input, and $y \in \Re^p$ is the output[2].

A fault is a deviation of at least one characteristic property under abnormal conditions that can make a system fail. A fault can cause an error which can result in failure ultimately [3]. The time dependent faults can be divided into abrupt, incipient, and intermittent faults (see fig. 1).

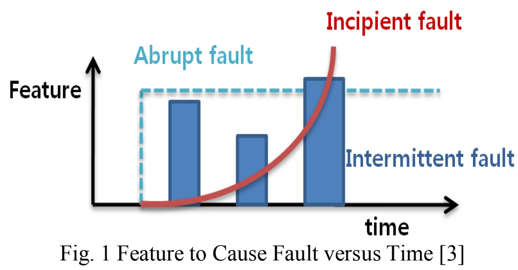

Fig. 1 Feature to Cause Fault versus Time [3]

Fault models can be classifiedas additive faults and multiplicative faults. Basic equations can be expressed by

Additive fault model: $Y(t) = Y_u(t) + f(t)$

Multiplicative fault model: $Y(t) = AU(A) + fU(t)$.

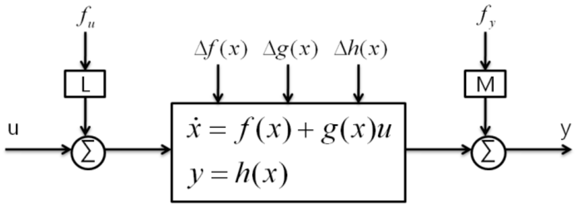

Fig. 2 System Models with Additive and Multiplicative Faults

Additive faults such as input faults f_u and output faults f_y in fig. 2 in the closed loop system model will be modeled by

$$\begin{aligned} \dot{x} &= f(x) + g(x)(u + Lf_u) = f(x) + g(x)u + g(x)Lf_u \\ y &= h(x) + Mf_y. \end{aligned} \quad (2)$$

Parametric faults which are multiplicative faults result in

$$\begin{aligned} \dot{x} &= f(x) + g(x)u + \left[\Delta f(x) + \Delta g(x)u\right] \\ y &= h(x) + \Delta h(x). \end{aligned} \quad (3)$$

Therefore, the nonlinear systems with faults can be physically modeled as equation (2) and equation (3).

B. Two Layered Fault Detection Methods

Fault detection determines fault existence and time of detection and its methods can be classifiedby limit checking, trend checking, model based detection, and data-driven detection [3].Each fault detection methodhas advantages and disadvantages. Parity equations are simple to design and to implement but they are problematic about robustness with regard to parameter changes. Parity equations cannot design faulty systems with multiplicative faults, too. State estimation can react very fast tosudden faults but state estimation is limited for nonlinear processes. On the other hand, parameter estimation is suitable for multiplicative faults[3].

Two layered fault detection allows for more precise detectionbecause it provides cross checks with different fault detection methods[4].Component level controllers use decentralized fault detection while systemlevel controllers apply centralized fault detection. The hybrid control unit of the hybrid electric vehicle will be a system level controller. If both detection methods are different, fault detection by cross checks can be precisely performed.

Component level controllers use general limit checking and trend checking. The thresholds for limit checking are mostly chosen by signal or process models and experimental data. Trend checking of the monitored variable is useful because it can be obtained earlier than detection time by limit checking of absolute value [3].

Normal fluctuations of measured signals are prohibited from generating fault alarm and fault deviation has to be detected quickly. The debouncing filter isolates transient fluctuations by limit checking over a prescribed period of debounce time. Fig. 3 shows an example of debouncing filters for minimizing faulty detection by fluctuations.

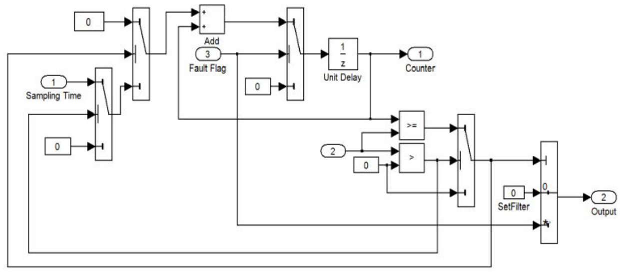

Fig. 3 TheDebouncing Filter for Fault Detection

Fault detection methods via stability analysis of nonlinear systems can be adapted for system level controllerssuch as the HCU in the hybrid electric vehicle (HEV). Fault detection via stability canalso produce control input and control stability effectively.

III. Fault Detection methods based on Stability for the HCU

Fault detection methods of system level controllers are usually different from fault detection methods of component level controllers. This section discusses fault detection methods via nonlinear stability analysisfor the HCU which is capable of detecting unknown parameter changes.

A. Fault Detection via Passivity or Dissipativity

Consider the affine nonlinear system

$$\begin{aligned} \dot{x} &= G(x(t), u(t), f(x)) + g(x)u + \Delta(x) \\ y &= h(x). \end{aligned} \quad (4)$$

A nonlinear system with $\Delta \equiv 0$ is passive if there exists a nonnegative Lyapunov function $V : X \to \Re$, with V(0)=0, called the storage function.Aninner product $\langle u(t), y(t) \rangle$, such that for all initial states, are the supplyrate[2]. Passivity and strict passivity can be described by

$$\langle u(t), y(t) \rangle \geq \beta (\text{passivity})$$

$$\langle u(t), y(t) \rangle \geq \delta |u|^2_{L_2 \text{ or } L_\infty} + \beta (\text{strict passivity})$$

The dissipativity inequality is given as

$$\underbrace{V(x(t)) - V(x(0))}_{\text{stored energy}} \leq \underbrace{\int_0^t W\left(y^T(s)u(s)\right)ds}_{\text{supplied energy}} \quad (5)$$

where $x(t)$ is the states at time t and $w(t) = w(u(t), y(t))$ is supply rate. If the inequality is violated, the control law is inadequate and the fault is generated. The energy dissipativity property can induce a fault detection law which is expressed by

$$Cr_{DISS} = V(x(t)) - V(x(0)) - \int_0^t W\left(y^T(s)u(s)\right)ds \quad (6)$$

If $Cr_{DISS} > 0$, a fault can be conjectured due to $Cr_{DISS} \leq 0$. Yang, Jiang, and Cocquempont (2010) presented several examples and adapted switching rules.

B. Fault Detection via Input-Output Stability

A system is called to have a finite gain, if there exists a constant $\gamma(\mathrm{H})<\infty$, which is the gain of H and a constant $\beta \in \Re^{+}$ such that

$$\left|y(t)\right|_{L_2\ or\ L_\infty} \le \gamma(H)\left|u(t)\right|_{L_2\ or\ L_\infty} + \beta \qquad (\because y(t)=Hu(t)).$$

Systems with finite gain are said to be finite-gain-stable[5].A fault detection rule via input-output stability property can be defined by

$$Cr_{IOS} = \left|y(t)\right|_{L_2 or L_\infty} - \left[\gamma(H)\left|u(t)\right|_{L_2 or L_\infty} + \beta\right] \tag{7}$$

This criterion helps high level controllers detect faults by comparison between input and output.

C.Fault Detection via Output-to-Input Stability

Systems with $f_a = 0$ are called output-input-stable, if there exists a positive integer N, a function β of class KL(decrescent function),and a function γ of class K_∞, such that for every initial state $\mathrm{x}(0)$ and every input $\mathrm{u} \in \ell^{N-1}$ (N-l order differentiable) its solution $\mathrm{x}(\mathrm{t})$ satisfies

$$\left|\begin{pmatrix} x(t) \\ u(t) \end{pmatrix}\right| \le \beta(\left|x(0)\right|,t) + \gamma\left(\left\|\underline{y}_N\right\|_{[0,t]}\right) \quad \text{for } \forall \mathrm{t} \tag{8}$$

where $\underline{y_k} = (y^T, \dot{y}^T, ..., y^{(k)T})^T$ [5][6]. The fault detection rule can be derived by

$$Cr_{OIS} = \left|\begin{pmatrix} x(t) \\ u(t) \end{pmatrix}\right| - \left[\beta(\left|x(0)\right|,t) + \gamma\left(\left\|\underline{y_N}\right\|_{[0,t]}\right)\right] \tag{9}$$

If $Cr_{DISS} > 0$, given system is unstable and any fault has been generated.

D.Fault Detection via Input-to-State Stability

The system with $f_a = 0$ is called Input-to-State-Stable [2][5],if there exist a function β of class KL,and a function γ of class K_∞, such that for every initial state $\mathrm{x}(0) \in \mathrm{D}$ and every input $\mathrm{u} \in D_u$ its solution $\mathrm{x}(\mathrm{t})$ satisfies

$$\left|x(t)\right| \le \beta(\left|x(0)\right|,t) + \gamma\left(\left\|u_T(\cdot)\right\|_{L_\infty}\right) \text{for } \forall t, 0 \le T \le t. \tag{10}$$

The fault detection rule can be formulated by

$$Cr_{ISS} = \left|x(t)\right| - \left[\beta(\left|x(0)\right|,t) + \gamma\left(\left\|u_T(\cdot)\right\|_{L_\infty}\right)\right] \tag{11}$$

The detection rule is useful to recognizefault existence between inputs and states.

IV. Application

A. Model of Interior PermanentMagnet Synchronous Motor

The IPMSM (Interior Permanent Magnet Synchronous Motor) has three-phase windings excited with a balanced three-phase current and can produce field torque and reluctance torque simultaneously. Since two types of torques are produced, the efficiency of IPMSM is relatively higher. That is the reason thatthe IPMSM is often applied as traction motors of the hybrid electric vehicle (HEV) and the electric vehicle. The model of IPMSM is as following [7][8]:

$$\begin{aligned} \dot{i}_q &= \frac{1}{L_q}\left[-ri_q + E_q - \omega_r\left(L_d i_d + \lambda_m\right)\right] \\ \dot{i}_d &= \frac{1}{L_d}\left[-ri_d + E_d + \omega_r L_q i_q\right] \\ \dot{\omega}_r &= \frac{3}{2J}\frac{P}{2}\left[\lambda_m i_q + \left(L_d - L_q\right)i_q i_d\right] - \frac{T_L}{J} \end{aligned} \tag{12}$$

where L, i, and E are inductances, currents, and voltages along q and d axes, respectively. r in equation (12) is resistance of the stator windings, ω_r is angular velocity of the rotor, J is inertia moment of the rotor, P is the number of poles, and T_L is the load torque from external load and friction.

The torque of the IPMSM is given as

$$T_{em} = \frac{3}{2}\frac{P}{2}\left[\lambda_m i_q + \left(L_d - L_q\right)i_q i_d\right].$$

Without considering parameter changes, the observer equations for adaptive control are expressed by

$$\begin{aligned} \dot{\hat{i}}_q &= \frac{1}{L_q}\left[-r\hat{i}_q + E_q - \omega_r\left(L_d\hat{i}_d + \lambda_m\right)\right] \\ \dot{\hat{i}}_d &= \frac{1}{L_d}\left[-r\hat{i}_d + E_d + \omega_r L_q\hat{i}_q\right] \\ \dot{\hat{\omega}}_r &= \frac{3}{2J}\frac{P}{2}\left[\lambda_m\hat{i}_q + \left(L_d - L_q\right)\hat{i}_q\hat{i}_d\right] - \frac{T_L}{J} + u \\ \tilde{y} &= \tilde{\omega}_r. \end{aligned} \tag{13}$$

u is the control input and $\hat{}$ is an estimated variable.Substituting equation (12) from equation (13) yields

$$\begin{aligned} \dot{\tilde{i}}_q &= \frac{1}{L_q}\left[-r\tilde{i}_q - \omega_r L_d\tilde{i}_d\right] \\ \dot{\tilde{i}}_q &= \frac{1}{L_d}\left[-r\tilde{i}_d + \omega_r L_q\tilde{i}_q\right] \\ \dot{\tilde{\omega}}_r &= \frac{3P}{4J}\left[\lambda_m\tilde{i}_q + \left(L_d - L_q\right)\tilde{i}_q\tilde{i}_q\right] + u \end{aligned} \tag{14}$$

where $\tilde{\omega}_r = \hat{\omega}_r - \omega_r$, $\tilde{i}_q = \hat{i}_q - i_q$ and $\tilde{i}_d = \hat{i}_d - i_d$.

ALyapunov function candidate is chosen by

$$V = \frac{1}{2}\tilde{i}_q^2 + \frac{1}{2}\tilde{i}_d^2 + \frac{1}{2}\tilde{\omega}_r^2$$

$$\dot{V} = -\frac{r}{L_q}\tilde{i}_q^2 - \frac{r}{L_d}\tilde{i}_d^2 - \left(\frac{L_d}{L_q} - \frac{L_q}{L_d}\right)\omega_r\tilde{i}_q\tilde{i}_d + \left[\frac{3P}{4J}\left[\lambda_m\tilde{i}_q + \left(L_d - L_q\right)\tilde{i}_q\tilde{i}_q\right] + u\right]\tilde{\omega}_r.$$

A control law can be defined by

$$u = -\frac{3P}{4J}\left[\lambda_m\tilde{i}_q + \left(L_d - L_q\right)\tilde{i}_q\tilde{i}_q\right] + \left(\frac{L_d}{L_q} - \frac{L_q}{L_d}\right)\tilde{i}_q\tilde{i}_q.$$

Then, $\dot{V} = -\frac{r}{L_q}\tilde{i}_q^2 - \frac{r}{L_d}\tilde{i}_d^2 \le 0$ .Since $V \ge 0$ and $\dot{V} \le 0$,

$\lim_{t\to\infty} V(t)$ exists and it is finite.Errors are L_∞ and L_2 .Therefore, all errors ($\tilde{i}_q, \tilde{i}_d$,and $\tilde{\omega}_r$) converge to zero while $t \to \infty$ by Barbalat'sLemma[6].

B. Simulation

The IPMSM is highly applicable for traction motors of the hybrid electric vehicles. The military hybrid electric vehicle has been developing for commercial and military applications and fig. 4 shows its prototype. An IPMSMequipped in the military hybrid electric vehicle with nominal parameters in Table 1 is simulated. The results of simulation areshown from figs 5 to 7. Initial errors of q axis and d axis currents are 35(A) and -5(A). Initial error of rotor speed is 20 (rad/s).

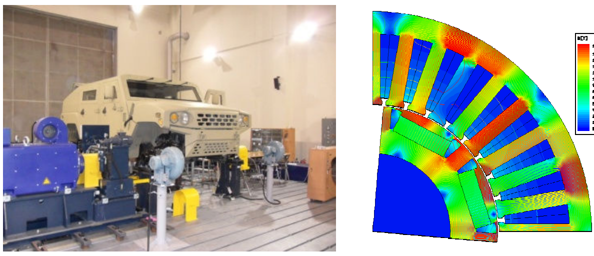

Fig. 4 A Military Hybrid Electric Vehicle and its IPMSM

TABLE I
IPMSM PARAMETERS

Parameters	Values
Rated output power (kW)	65
Magnetic flux linkage(Wb)	0.533
Number of poles	8
Stator resistance (ohm)	2.875
q-axis inductance (mH)	456
d-axis inductance (mH)	216
Inertia (kg-m^2)	0.069

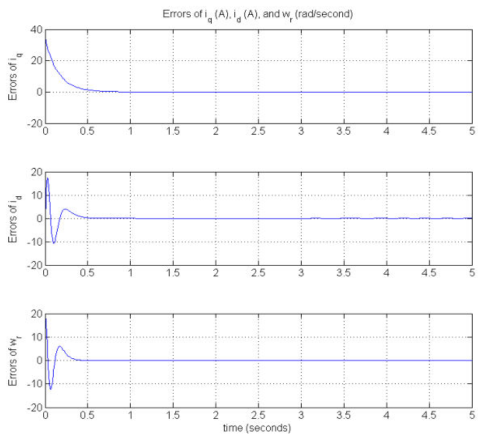

Fig. 5 Simulated Dynamic Errors of Operation Variables

In fig. 6, Lyapunov function exists in positive range but the derivative of Lyapunov function locates at negative range.Therefore, the system is stable without any fault.

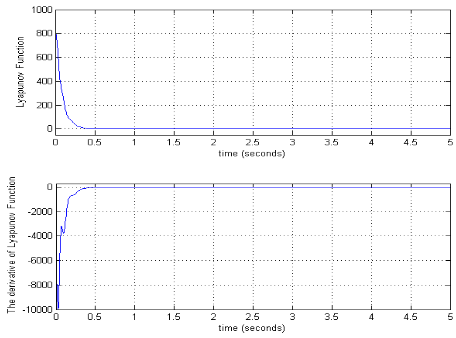

Fig. 6 Lyapunov Function and its Derivative

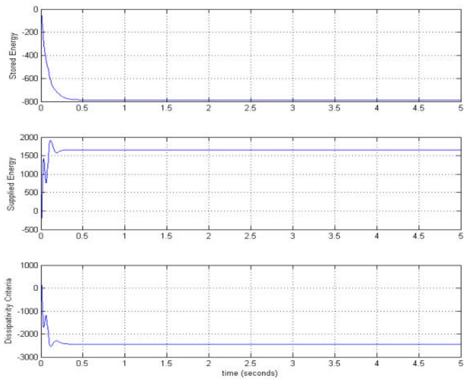

Fig. 7 Stored and Supplied Energy from Equation (5) and Dissipativity Criteria from Equation (6)

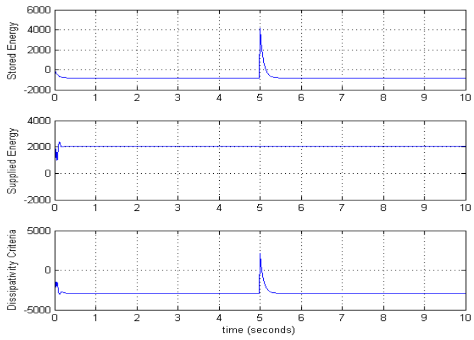

Fig. 8 Fault Detection Performance via Disspativity Criteria

Fig. 8 shows fault detection byunpermittedactual current changefrom 0(A) to 100(A) along q-axis at 5s. Since the dissipativity criterioncrosses over zero at 5s, the fault is detected in fig. 8. Using dissipativity stability, fault detection can be achieved effectively.

V. CONCLUSION

This paper proposed two layered fault detection methods to enhance the reliability and safety of the system.Two layered fault detection by component level controllers and system level controllers were defined. Component level controllers detected fault bylimit checking, trend checking, and model-based detection. The debouncing filter for avoiding faulty alarm by transient fluctuation was discussed. System level controllers used fault detection methods via stability analysis which can detect unknown changes and compare with fault signals from lower level controllers.Fault detection methods and detection criteria via stabilityin nonlinear systems were developed and were applied to the HCU in orderto detect faults of the traction motor,an IPMSM.

Fault detections via stability have limitation about fault isolation even though the fault detection method is helpful to check faults by unknown features. As future work, improving detection performance with changing different pairs between system level FDD and component level FDD has to be preceded. Integrated FDD will be designed and implemented inthe hybrid control unit of the hybrid electric vehicle.

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