2009 American Control Conference
Hyatt Regency Riverfront, St. Louis, MO, USA
June 10-12, 2009

Model-based fault diagnosis for a vehicle chassis system

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***Abstract*—Based on a linearized 3-DOF bicycle model, this paper compares two different fault detection and isolation (FDI) methods for the FDI of a command input fault and an output sensor fault within a vehicle chassis system. The first FDI approach uses parity equations to decouple the two types of faults, while at the same time, minimizes the influence of the disturbance on the residuals. The second FDI method uses sliding mode observer design, and by monitoring the equivalent control of the observers, in which the fault information is contained, achieves the detection and isolation of the faults. Lane change maneuvers are simulated, and the results showed that, under the given simulation condition, both diagnostic approaches can successfully detect and isolate the two types of faults despite the existence of a lateral wind gust disturbance.**

I. INTRODUCTION

WITH the increasing speed of the modern vehicle, hand -ling and stability issues are of indisputable significance. Vehicle control systems such as VSC/ESP are implemented to guarantee the handing and stability of the vehicle especially at high speed and when the vehicle is under cornering maneuvers. In the popular VSC/ESP system, the control system utilizes the information of the steering angle from the driver, the vehicle's yaw rate and lateral acceleration to decide the control of the actuators, which makes the diagnosis of the actuator fault and sensor fault especially important. In [1]a hierarchi- -cal model-based FDI scheme for fault detection and isolation for a vehicle system is presented, and in the subsystem's FDI unit, the possibility of estimating the state of the vehicle has been demonstrated for a simplified front wheel steered bicycle model based on continuous time sliding mode observers. H. Fennel [2] developed a model based sensor monitoring system for ESP that was implemented, and it is currently produced in large volumes by Continental TEVES. The monitoring system is mainly used for detecting faults in sensors only.

Since the field of FDI has seen significant progress with respect to model-based algorithmic approaches to residual generation, this paper utilized this relatively mature approach to construct the FDI scheme for fault detection and isolation of a command input fault and an output sensor fault within a vehicle chassis system. A parity equation residual generation method is presented as basis of the FDI scheme, and compared with a linear sliding mode observer based approach. By monitoring the equivalent control of the observers, in which the fault information is contained, the detection and isolation of the input fault and output fault is achieved. The analytical relationship between the faults and the equivalent control is analyzed, and the faults are further decoupled using transformation.

The paper is organized as follows. The "Model Description" section describes the nonlinear vehicle chassis model. In the "Diagnostic Approach" section, two FDI methods are presented, one using the classical Parity Equation, and the other using Sliding Mode Observers. Simulations are then carried in the subsequent section, where both FDI methods are verified.

Manuscript received September 12, 2008.

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II. NOMENCLATURE

a	distance from center of gravity to front axle
b	distance from center of gravity to rear axle
L	wheelbase
r	yaw velocity
V_x	forward velocity
V_y	lateral (sideslip) velocity
α_f	slip angle of the front tires
α_r	slip angle of the rear tires
δ	front axle steering angle
M_S	Sprung mass
M_{US}	Unsprung mass
M	Total mass of the vehicle
k_s	Suspension stiffness N-m per radian of roll
c_s	Suspension damping N-m per rad/s of roll rate
h_s	Height of CG from roll axis

III. MODEL DESCRIPTION

A bicycle model of the vehicle chassis system that includes rolling motion is considered.

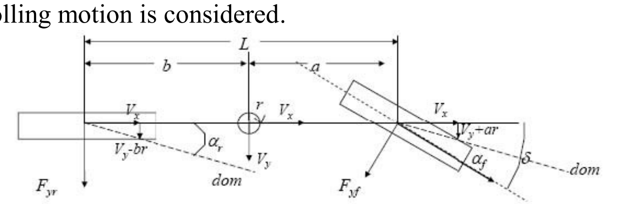

Fig. 1. Bicycle model.

The vehicle model is designed to have three degrees of freedom (3-DOF), these are: sideslip velocity V_y, yaw rate r, and roll angle ϕ. The input to the system is the steering angle of the front wheels. The measured outputs are yaw rate r and lateral acceleration a_y [3], [4].

The slip angles α_f and α_r are given by

$$\alpha_f = \delta - \left(\frac{V_y + ar}{V_x} \right), \alpha_r = \beta_{rr} \bullet \phi - \left(\frac{V_y - br}{V_x} \right) \tag{1}$$

where β_{rr} = degree rear steering per degree roll.

The nonlinear vehicle chassis model is expressed using the following state space equation:

$$\begin{aligned} &\begin{bmatrix} 1 & 0 & \frac{M_s h_s \cos(\phi)}{M} & 0 \\ 0 & \frac{I_{zzo}}{M} & \frac{I_{xzso}\cos(\phi)}{M} & 0 \\ \frac{M_s h_s \cos(\phi)}{M} & \frac{I_{xzso}\cos(\phi)}{M} & \frac{I_{xxso}}{M} & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \dot{V}_y \\ \dot{r} \\ \ddot{\phi} \\ \dot{\phi} \end{bmatrix} = \begin{bmatrix} \frac{1}{M} & \frac{1}{M} \\ \frac{a}{M} & \frac{-b}{M} \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} F_{yf} \\ F_{yr} \end{bmatrix} \\ &+ \begin{bmatrix} \frac{M_s h_s}{M}\sin(\phi) r^2 - V_x r + \frac{M_s h_s}{M}\sin(\phi)\dot{\phi}^2 \\ -r\left(\frac{M_s h_s^2}{M}\sin(2\phi)\dot{\phi} + \frac{M_s h_s}{M}\sin(\phi) V_y \right) + \frac{I_{xzso}}{M}\sin(\phi)\dot{\phi}^2 \\ -\frac{M_s h_s V_x}{M}\cos(\phi) r + \frac{M_s h_s^2}{2M}\sin(2\phi) r^2 - \frac{c_s}{M}\dot{\phi} + \frac{M_s h_s g}{M}\sin(\phi) - \frac{k_s}{M}\phi \\ \dot{\phi} \end{bmatrix} \end{aligned} \tag{2}$$

The only input to the model is actually the steering command δ coming from the driver (since the longitudinal speed, i.e. throttle position is assumed to be constant). However, the force-slip angle relation of a tire can be best modeled according to the Pacejka tire model, which leads the lateral forces F_{yf} and F_{yr} to be treated as inputs. Then, further associating the slip angles with the steering angle δ by (1) would finally result in the nonlinear vehicle model where the steering angle is the only input.

IV. Problem Formulation

This paper deals with the detection and isolation of the following set of faults:

- Fault on the steering angle command (actuator fault). The effective steering angle does not correspond to the commanded steering angle. Our objective is to detect a constant error of 0.1 degree or higher.
- Yaw rate fault (sensor fault). Our objective is to detect a bias of 15% or more from the nominal value of the yaw rate.

The longitudinal velocity of the modeled vehicle is set to a constant value of 100km/h. A wind gust disturbance up to 1500N is also considered to be acting on the system. We assume also that the lateral acceleration is measurable and fault free. For both yaw rate and lateral acceleration sensors a 5% white Gaussian noise is considered.

V. Model Linearization

As the vehicle model is simulated under the assumption of constant longitudinal velocity of 100km/h, which is a very high speed, the steering maneuver is bounded to be a small steering angle input. By linearizing the system model around $\begin{pmatrix} V_{y0} & r_0 & \dot{\phi}_0 & \phi_0 \end{pmatrix} = \begin{pmatrix} 0 & 0 & 0 & 0 \end{pmatrix}$ and $\delta_0 = 0$, we are expecting good approximation of the nonlinear vehicle model.

The nonlinear model in Section 3 can finally be linearized and put into standard state-space in the form of

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}u \tag{3}$$

$$\mathbf{y} = \mathbf{C}\mathbf{x} + \mathbf{D}u \tag{4}$$

where $u = \delta$, $\mathbf{x} = \begin{bmatrix} V_y & r & \dot{\phi} & \phi \end{bmatrix}^{\mathrm{T}}$ is the state, and $\mathbf{y}$ is the output.

As can be verified by simulation, the linearized model presents good approximation of the nonlinear model under small input case. The proposed diagnostic algorithm may be based on this linear model. However, when larger input is fed into the system or when the assumed constant system parameter, vehicle longitudinal velocity varies, modelling error issue would thus arise. To deal with this issue, multiple linearized models can be constructed in the Linearized Models module, providing the possibility of more precise approximation of the real nonlinear model at any time by selecting appropriate linearized model according to the system operating region.

VI. Diagnostic algorithm design

A. *First method: Parity Equation (PE)*

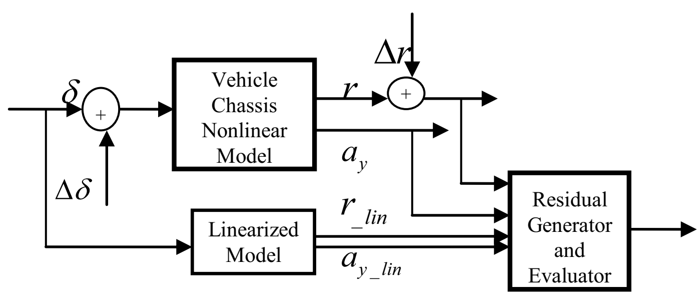

Fig. 2 PE based FDI scheme.

Fig. 2 shows the Parity Equation based FDI scheme, where $\Delta\delta$ is the input fault, and Δr is the output fault. The command input δ goes into the linearized model, which generates the outputs $r_{\_lin}, a_{y\_lin}$. The Residual Generator and Evaluator takes the outputs of both the nonlinear and linear models and then generate and evaluate the residuals to make a decision on the presence of a fault or not.

The linearized model given by (3) and (4) can be expressed in the general state space equation form as

$$\begin{aligned} \dot{\mathbf{x}} &= \mathbf{A}\mathbf{x} + \mathbf{B}u + \mathbf{E}_{\mathbf{F}}\mathbf{p} + \mathbf{E}_{\mathbf{D}}q \\ \mathbf{y} &= \mathbf{C}\mathbf{x} + \mathbf{D}u + \mathbf{F}_{\mathbf{F}}\mathbf{p} + \mathbf{F}_{\mathbf{D}}q \end{aligned} \tag{5}$$

where $\mathbf{p}$ is the fault vector, and q is the disturbance.

The system given by (5) can be expressed in terms of transfer functions in the frequency domain as:

$$\mathbf{Y}(s) = \mathbf{M}(s)U(s) + \mathbf{S_F}(s)\mathbf{p}(s) + \mathbf{S_D}(s)q(s) \tag{6}$$

Where

$$\mathbf{M}(s) = \mathbf{C}\left[s\mathbf{I} - \mathbf{A}\right]^{-1}\mathbf{B} + \mathbf{D},\ \mathbf{S_F}(s) = \left[\ \mathbf{M}(s) \middle| \begin{matrix} 1 \\ 0 \end{matrix}\right] \tag{7}$$

and $\mathbf{p}(s) = \left[p_1(s) \quad p_2(s)\right]^T = \left[\Delta U(s) \quad \Delta Y_1(s)\right]^T$

The residuals are given by [5]:

$$\begin{bmatrix} R_1(s) \\ R_2(s) \end{bmatrix} = \mathbf{W}(s)\left[\mathbf{Y}(s) - \mathbf{M}(s)U(s)\right] = \mathbf{W}(s)\left[\mathbf{S_F}(s)\mathbf{p}(s) + \mathbf{S_D}(s)q(s)\right]$$

$$= \begin{bmatrix} w_{11}(s) & w_{12}(s) \\ w_{21}(s) & w_{22}(s) \end{bmatrix} \left\{ \left[\begin{array}{c|c|c} M_1(s) & 1 & S_{D1}(s) \\ M_2(s) & 0 & S_{D1}(s) \end{array}\right] \begin{bmatrix} p_1(s) \\ p_2(s) \\ q(s) \end{bmatrix} \right\} \tag{8}$$

Our objective is to design w_{ij} $(i, j = 1, 2)$ such that the residuals have desired responses to the faults and disturbance given by z_{kl} $(k = 1, 2; l = 1, 2, 3)$, i.e.

$$\begin{bmatrix} R_1(s) \\ R_2(s) \end{bmatrix} = \begin{bmatrix} z_{11}(s) & z_{12}(s) & z_{13}(s) \\ z_{21}(s) & z_{22}(s) & z_{23}(s) \end{bmatrix} \begin{bmatrix} p_1(s) \\ p_2(s) \\ q(s) \end{bmatrix} \tag{9}$$

Note that decoupling the disturbance would put restriction on the further decoupling of the faults. That is, if we set $z_{13}(s) = w_{11}(s)S_{D1}(s) + w_{12}(s)S_{D2}(s) = 0$ and $z_{23}(s) = w_{21}(s)S_{D1}(s) + w_{22}(s)S_{D2}(s) = 0$ for decoupling the disturbance, it is not possible to further decouple the two types of faults from each other.

Here, first the problem of decoupling the two faults is considered, then, by adjusting $\mathbf{W}(s)$, the influence of the disturbance on the residuals is minimize.

To decouple the two types of faults, we design:

$$\begin{bmatrix} z_{11}(s) & z_{12}(s) \\ z_{21}(s) & z_{22}(s) \end{bmatrix} = \begin{bmatrix} \dfrac{1}{\tau_1 s + 1} & 0 \\ 0 & \dfrac{1}{\tau_2 s + 1} \end{bmatrix} \tag{10}$$

Then, by neglecting the disturbance, the secondary residuals become

$$\begin{bmatrix} R_1(s) \\ R_2(s) \end{bmatrix} = \begin{bmatrix} \dfrac{1}{\tau_1 s + 1} p_1 & \dfrac{1}{\tau_2 s + 1} p_2 \end{bmatrix}^T \tag{11}$$

where τ_1, τ_2 can be selected to adjust the transient response of the residuals to the faults, and the transfer function of the disturbance to the residuals, i.e. $z_{13}(s)$, $z_{23}(s)$, as well. Furthermore, the steady state value of the residual would be identical to the magnitude of the corresponding fault itself. From (8) and (9), by neglecting q, it follows that:

$$\begin{bmatrix} w_{11}(s) & w_{12}(s) \\ w_{21}(s) & w_{22}(s) \end{bmatrix} = \begin{bmatrix} z_{11}(s) & z_{12}(s) \\ z_{21}(s) & z_{22}(s) \end{bmatrix} \mathbf{S_F}^{-1}(s)$$

Once the matrix $\mathbf{W}(s)$ is determined, it is possible to evaluate the influence of the disturbance on the residual by calculating and analyzing $z_{13}(s)$, $z_{23}(s)$.

Fig. 3 represents the Bode plots of $z_{13}(s)$ ($z_{23}(s)$ can be plotted in a similar way) when $\tau_1 = 1$. The maximum of the magnitude of both $z_{13}(s)$ and $z_{23}(s)$ are reached at frequency 10(rad/sec), with the value -120dB and -100dB respectively. Note that $z_{13}(s)$, $z_{23}(s)$ depend only on τ_1, τ_2 respectively, which can be selected independently.

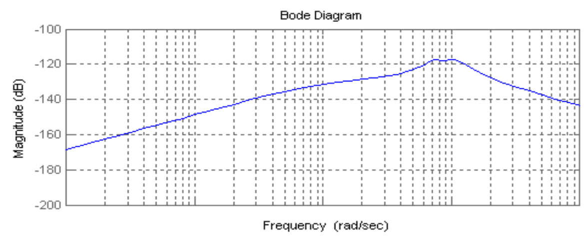

Fig. 3 Bode Plots of $z_{13}(s)$ when $\tau_1 = 1$

Balancing between the response of the residuals to the faults and the purpose of minimizing the magnitude of $z_{13}(s)$ and $z_{23}(s)$, the time constants are finally chosen to be $\tau_1 = 2$ and $\tau_2 = 1$.

B. Second method: Sliding mode observer (SMO)

This approach is based on a Dedicated Observer Scheme (DOS) and uses the two outputs to build two sliding mode observers, each using one output [6],[7]. In this case the fault information is included in the equivalent control of the sliding mode observers, and by its magnitude, it is possible to achieve the fault detection and isolation [8]. Since one output is fault free (a_y), the sliding mode observer using this output is robust to the output sensor fault and thus can be designed to only detect the input fault. The other observer which uses the output information including sensor fault (r) can be used to isolate the output fault.

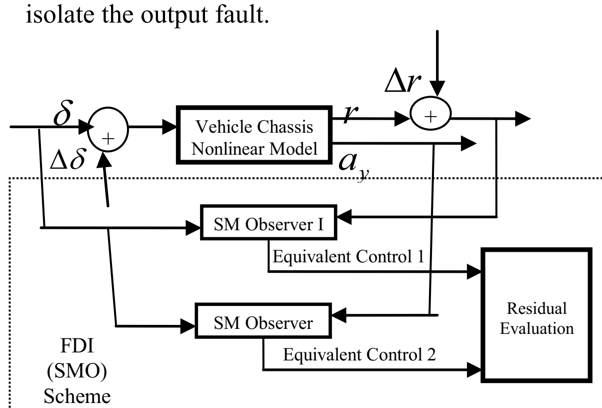

Fig. 4 Sliding Mode Observer based FDI scheme.

1) Design of SMO I

Take the first output, i.e. yaw rate sensor measurement

$y_1 = r$

The system state-space equation reads [9]

$$\begin{aligned}\dot{\mathbf{x}} &= \mathbf{A}\mathbf{x} + \mathbf{B}(u+\Delta u) + \mathbf{E_D} q \\ y_{1m} &= y_1 + \Delta y = \mathbf{C}_1\mathbf{x} + \Delta y\end{aligned} \tag{12}$$

Let $\mathbf{x}_1 = \begin{bmatrix} V_y & \dot{\phi} & \phi \end{bmatrix}^{\mathrm{T}}$, and define the new state vector of the system as $\begin{bmatrix} \mathbf{x}_1 & y_1 \end{bmatrix}^{\mathrm{T}}$. Introduce the transformation matrix $\mathbf{T}$ such that: $\begin{bmatrix} \mathbf{x}_1 \\ y_1 \end{bmatrix} = \mathbf{T}\mathbf{x}$

By applying the transformation to (, we obtain

$$\begin{aligned}\dot{\mathbf{x}}_1 &= \mathbf{A}_{11}\mathbf{x}_1 + \mathbf{A}_{12} y_1 + \mathbf{B}_1(u+\Delta u) + \mathbf{E}_{\mathbf{d}1} q \\ \dot{y}_1 &= \mathbf{A}_{21}\mathbf{x}_1 + \mathbf{A}_{22} y_1 + \mathbf{B}_2(u+\Delta u) + \mathbf{E}_{\mathbf{d}2} q \\ y_{1m} &= y_1 + \Delta y\end{aligned} \tag{13}$$

where

$$\mathbf{T}A\mathbf{T}^{-1} = \begin{bmatrix} \mathbf{A}_{11} & \mathbf{A}_{12} \\ \mathbf{A}_{21} & \mathbf{A}_{22} \end{bmatrix}, \mathbf{T}B = \begin{bmatrix} \mathbf{B}_1 \\ \mathbf{B}_2 \end{bmatrix}, \mathbf{T}\mathbf{E}_{\mathbf{d}} = \begin{bmatrix} \mathbf{E}_{\mathbf{d}1} \\ \mathbf{E}_{\mathbf{d}2} \end{bmatrix}$$

Consider now the observer I represented by

$$\begin{aligned}\dot{\hat{\mathbf{x}}}_1 &= \mathbf{A}_{11}\hat{\mathbf{x}}_1 + \mathbf{A}_{12}\hat{y}_1 + \mathbf{B}_1 u - L_1 v_1 \\ \dot{\hat{y}}_1 &= \mathbf{A}_{21}\hat{\mathbf{x}}_1 + \mathbf{A}_{22}\hat{y}_1 + \mathbf{B}_2 u + v_1\end{aligned} \tag{14}$$

where v_1 is an auxiliary input defined by

$$v_1 = M_1 \operatorname{sign}\left(y_{1m} - \hat{y}_1\right) \tag{15}$$

Define the errors as $e_y = y_{1m} - \hat{y}_1$, $e_1 = x_1 - \hat{x}_1$, then

$$\begin{aligned}\dot{e}_y &= \dot{y}_{1m} - \dot{\hat{y}}_1 = \dot{y}_1 + \Delta\dot{y} - \dot{\hat{y}}_1 = \\ &= \mathbf{A}_{21} e_1 + \mathbf{A}_{22}\left(e_y - \Delta y\right) + \mathbf{B}_2\Delta u + \mathbf{E}_{\mathbf{d}2} q + \Delta\dot{y} - M_1 \operatorname{sign}\left(e_y\right)\end{aligned} \tag{16}$$

Convergence conditions are given by [10], [11]. When M_1 is large enough, it can be shown that $e_y = 0$ after a short transient.

The equivalent control v_{eq1} can be obtained from (16) as:

$$v_{eq1} = \mathbf{A}_{21} e_1 - \mathbf{A}_{22}\Delta y + \mathbf{B}_2\Delta u + \mathbf{E}_{\mathbf{d}2} q + \Delta\dot{y} \tag{17}$$

On the sliding manifold $e_y = 0$

$$\begin{aligned}\dot{e}_1 &= \dot{\mathbf{x}}_1 - \dot{\hat{\mathbf{x}}}_1 = \left(\mathbf{A}_{11} + L_1\mathbf{A}_{21}\right) e_1 - \left(\mathbf{A}_{12} + L_1\mathbf{A}_{22}\right)\Delta y \\ &+ \left(\mathbf{B}_1 + L_1\mathbf{B}_2\right)\Delta u + \left(\mathbf{E}_{\mathbf{d}1} + L_1\mathbf{E}_{\mathbf{d}2}\right) q + L_1\Delta\dot{y}\end{aligned} \tag{18}$$

The steady state value of e_1 after the transient can be expressed as:

$$e_{1ss} = k_y\Delta y + k_u\Delta u + k_q \cdot q + k_{ydot}\Delta\dot{y} \tag{19}$$

where k_y, k_u, k_q, k_{ydot} are coefficients parameterized by L_1.

By substituting (19) into (17), we get

$$\begin{aligned}v_{eq1} &= \left(\mathbf{A}_{21} k_u + \mathbf{B}_2\right)\Delta u + \left(\mathbf{A}_{21} k_y - \mathbf{A}_{22}\right)\Delta y \\ &+ \left(\mathbf{A}_{21} k_q + \mathbf{E}_{\mathbf{d}2}\right) q + \left(\mathbf{A}_{21} k_{ydot} + 1\right)\Delta\dot{y}\end{aligned} \tag{20}$$

By adjusting L_1, it is possible to make k_q and k_{ydot} relatively small, so that the equivalent control of the first sliding mode observer will be mainly constituted by two parts (neglecting the derivative term and disturbance): a term proportional to the input fault Δu, and a second term proportional to the output fault Δy.

2) Design of SMO II

Take the second output, i.e. lateral acceleration sensor measurement, we have $y_2 = a_y$.

The system state-space equation reads:

$$\begin{aligned}\dot{\mathbf{x}} &= \mathbf{A}\mathbf{x} + \mathbf{B}(u+\Delta u) + \mathbf{E}_{\mathbf{d}} q \\ y_2 &= \mathbf{C}_2\mathbf{x} + \mathbf{D}_2(u+\Delta u) + \mathbf{F}_{\mathbf{d}}^{(r2)} q\end{aligned} \tag{21}$$

$\mathbf{C}_2, \mathbf{D}_2, \mathbf{F}_{\mathbf{d}}^{(r2)}$ are the second row of $\mathbf{C}, \mathbf{D}, \mathbf{F}_{\mathbf{d}}$ respectively, as given by (5).

Define $y_{2m} = y_2 - \mathbf{D}_2 u, y_s = \mathbf{C}_2\mathbf{x}$, and consider the new state vector $\begin{bmatrix} \overline{\mathbf{x}}_1 & y_s \end{bmatrix}^{\mathrm{T}}$, where $\overline{\mathbf{x}}_1 = \begin{bmatrix} V_y & r & \dot{\phi} \end{bmatrix}^{\mathrm{T}}$.

By performing the state transformation similar to that in the first case, we can rewrite (21) as

$$\begin{aligned}\dot{\overline{\mathbf{x}}}_1 &= \mathbf{A}_{11}\overline{\mathbf{x}}_1 + \mathbf{A}_{12} y_s + \overline{\mathbf{B}}_1(u+\Delta u) + \overline{\mathbf{E}}_{\mathbf{d}1} q \\ \dot{y}_s &= \mathbf{A}_{21}\overline{\mathbf{x}}_1 + \mathbf{A}_{22} y_s + \overline{\mathbf{B}}_2(u+\Delta u) + \overline{\mathbf{E}}_{\mathbf{d}2} q \\ y_{2m} &= y_s + \mathbf{D}_2\Delta u + \mathbf{F}_{\mathbf{d}}^{(r2)} q\end{aligned} \tag{22}$$

where $\overline{\mathbf{A}}_{ij}, \overline{\mathbf{B}}_i, \overline{\mathbf{E}}_{\mathbf{d}i}(i, j = 1, 2)$ are some constant matrices obtained by performing the transformation.

Similarly to the first case, the observer II is constructed and its equivalent control can be finally obtained as:

$$\begin{aligned}v_{eq2} &= \left(\overline{\mathbf{A}}_{21}\overline{k}_u + \overline{\mathbf{B}}_2 - \overline{\mathbf{A}}_{22}\mathbf{D}_2\right)\Delta u + \left(\overline{\mathbf{A}}_{21}\overline{k}_{udot} + \mathbf{D}_2\right)\Delta\dot{u} \\ &+ \left(\overline{\mathbf{A}}_{21}\overline{k}_q + \overline{\mathbf{E}}_{\mathbf{d}2} - \overline{\mathbf{A}}_{22}\mathbf{F}_{\mathbf{d}}^{(r2)}\right) q + \left(\overline{\mathbf{A}}_{21}\overline{k}_{qdot} + \mathbf{F}_{\mathbf{d}}^{(r2)}\right)\dot{q}\end{aligned} \tag{23}$$

Where $\overline{k}_u, \overline{k}_{udot}, \overline{k}_q, \overline{k}_{qdot}$ can be adjusted by tuning L_2.In practice, the term $\Delta\dot{u}$ is very small, so this term can be neglected. If, by design, the coefficient of the disturbance and its derivative are made relatively small, then the equivalent control of the second sliding mode observer would be proportional to the input fault Δu. This is possible because of the free parameter L_2.

From (20) and (23) , we have then

$$v_{eq1} = \left(\mathbf{A}_{21} k_u + \mathbf{B}_2\right)\Delta u + \left(\mathbf{A}_{21} k_y - \mathbf{A}_{22}\right)\Delta y = k_{ueq1}\Delta u + k_{yeq1}\Delta y \tag{24}$$

$$v_{eq2} = \left(\overline{\mathbf{A}}_{21}\overline{k}_u + \overline{\mathbf{B}}_2 - \overline{\mathbf{A}}_{22}\mathbf{D}_2\right)\Delta u = k_{ueq2}\Delta u \tag{25}$$

To decouple the two types of faults, consider the following transformation

$$\begin{bmatrix} r_1 \\ r_2 \end{bmatrix} = \bar{T} \begin{bmatrix} v_{eq1} \\ v_{eq2} \end{bmatrix} = \begin{bmatrix} \Delta u \\ \Delta y \end{bmatrix} \tag{26}$$

$$\begin{bmatrix} r_1 \\ r_2 \end{bmatrix} = \bar{T} \begin{bmatrix} k_{ueq1}\Delta u + k_{yeq1}\Delta y \\ k_{ueq2}\Delta u \end{bmatrix} = \bar{T} \begin{bmatrix} k_{ueq1} & k_{yeq1} \\ k_{ueq2} & 0 \end{bmatrix} \begin{bmatrix} \Delta u \\ \Delta y \end{bmatrix} = \begin{bmatrix} \Delta u \\ \Delta y \end{bmatrix}$$
$$\Rightarrow \bar{T} = \begin{bmatrix} \bar{T}_{11} & \bar{T}_{12} \\ \bar{T}_{21} & \bar{T}_{22} \end{bmatrix} = \begin{bmatrix} k_{ueq1} & k_{yeq1} \\ k_{ueq2} & 0 \end{bmatrix}^{-1} \tag{27}$$

Then the residuals r_1, r_2 will each contain only one fault (neglecting those minor terms), thus achieving the fault isolation.

VII. Simulation Results

For our simulation process, we considered a disturbance acting on the system as represented in Fig. 5:

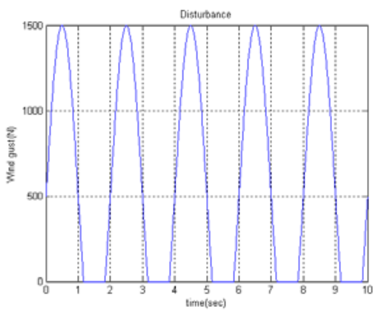

Fig. 5 Disturbance time history

A. Parity Equation approach

The simulation results under different fault/disturbance conditions using PE-based approach are shown in Fig. 6~Fig. 8. In all cases, the driver is doing a passing maneuver, i.e. first changing to the left lane, and then changing back to the right lane.

TABLE I
PHYSICAL PARAMETERS USED IN THE PRESENT MODEL

Parameter	Value
Distance from center of gravity to front axle a	1.14 m
Distance from center of gravity to rear axle b	1.4 m
Forward velocity V_x	100 km/h
Sprung mass M_S	1363.64 kg
Unsprung mass M_{US}	136.36 kg
Suspension stiffness k_s	40107 N.m/radian of roll
Suspension damping c_s	1203.2 N.m per rad/s of roll rate
Height of CG from roll axis h_c	0.35 m
rear steering per degree roll β_{rf}	-0.095 degree

Fig. 6 shows the case when no fault is present, where the two residuals, with or without the disturbance, stay within the upper and lower thresholds. For the first residual r_1, the upper and lower threshold $th_1 = \pm 0.0012$; for the second residual r_2, $th_2 = \pm 0.012$. In Fig. 7, an input fault (p1) occurs at 2.5s, which is a constant 0.1 degree deviation from the nominal input. Since the there is no output fault, $|r_2|$ stay below th_2, while $|r_1|$ exceeds th_1 at 5s, indicating the input fault occurs. In Fig. 8, a 15% bias from the nominal value of the yaw rate occurs at the yaw rate sensor from 5s, which constitute the output fault (p2 for sensor fault without disturbance and p2 w/d for fault with disturbance). Note that this fault is proportional to the nominal value of the yaw rate, so the fault really occurs at 10s when the yaw rate is relatively large. r_2 exceeds th_2 at 10.7s.

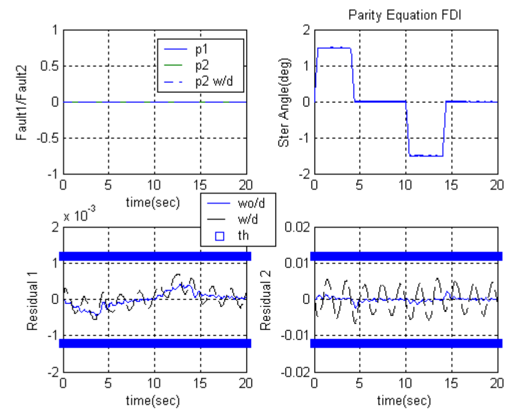

Fig. 6. Residuals under no fault condition.

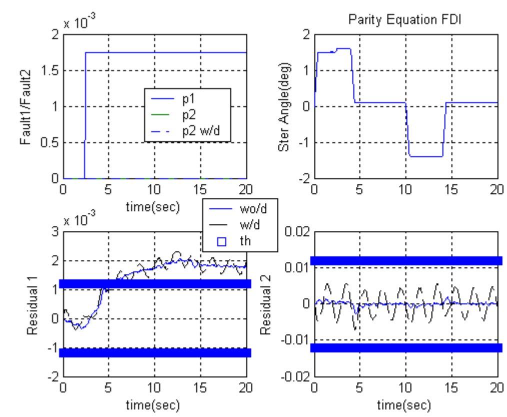

Fig. 7. Residuals under input fault (constant 0.1 degree).

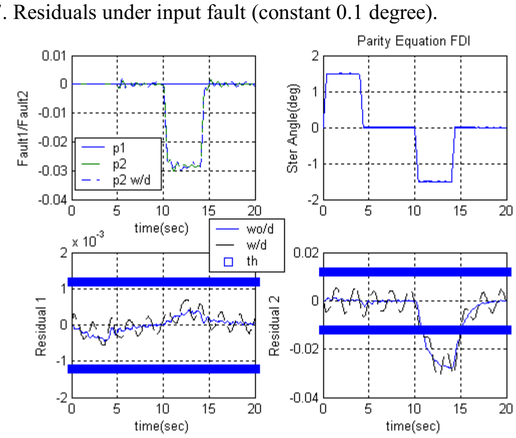

Fig. 8. Residuals under output fault (+15% from nominal value).

We define the fault signatures as

$$s_1 = \begin{cases} 1 & \text{if } |r_1| > th_1 \\ 0 & \text{if } |r_1| \le th_1 \end{cases} \qquad s_2 = \begin{cases} 1 & \text{if } |r_2| > th_2 \\ 0 & \text{if } |r_2| \le th_2 \end{cases}$$

The FDI rule is simply as stated in Table 1.

TABLE 1. FAULT SIGNATURE FOR PE SCHEME

Fault Type	S_1	S_2
No fault	0	0
Input Fault	1	0
Output Fault	0	1
Both Faults	1	1

B. *Sliding Mode Observer approach*

Similar simulation results using SMO-based approach are shown in Fig. 9~Fig. 11.

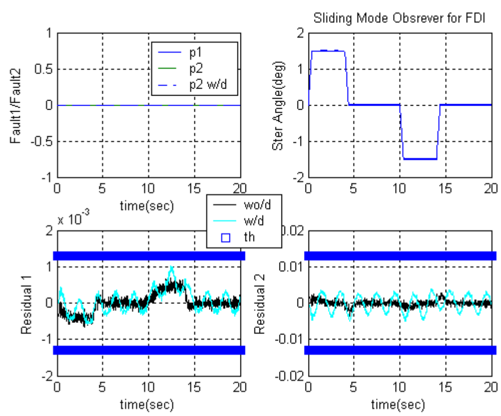

Fig. 9. Residuals under no fault condition.

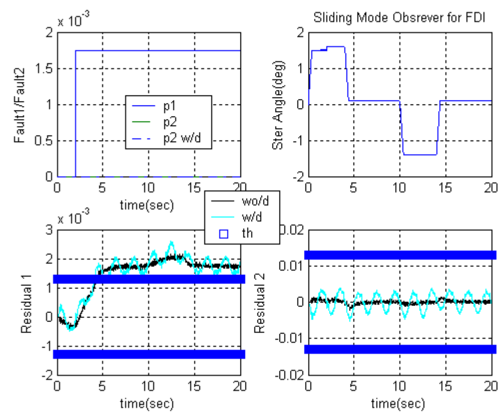

Fig. 10. Residuals under input fault (constant 0.1 degree).

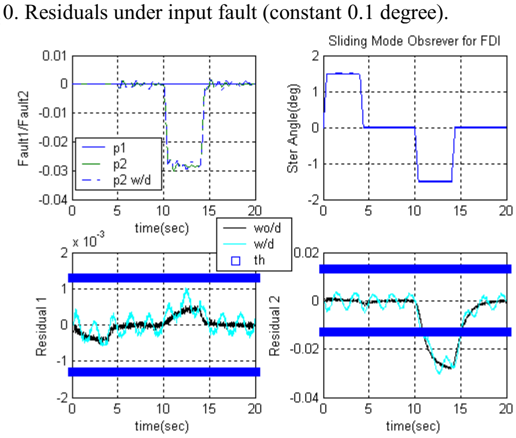

Fig. 11. Residuals under output fault (+15% sensor fault).

The same FDI rule for the PE based approach can be applied.

Compared to the PE method, the residuals using SMO method present chattering when the two methods have comparable transient responses. Note however, that, when the actual vehicle speed is not a constant 100km/h any more, the coefficient matrices in (5) will change, causing phenomenon model error for PE-based approach. On the contrary for the SMO method, which is a time-variant approach in nature, the coefficient matrices in (12) and (21) can be updated with time according to the real time vehicle speed.

VIII. CONCLUSION

This paper presents two fault diagnostic approaches for the fault detection/isolation of a vehicle chassis system in the presence of actuator fault and output sensor fault, and under the influence of wind gust disturbances. Both approaches use the same linearized model from the nonlinear vehicle chassis model as their FDI basis.

In this paper, the relationship between the faults and the equivalent control is analyzed. Simulations are carried for both approaches. As the simulation results showed, under the same conditions, both diagnostic approach can successfully detect and isolate the two types faults despite the existence of the disturbance.

Further work will account for the model error and accommodate the operation region further away from the linearized point, making the FDI system more general and robust.

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