Mode Identification for Hybrid Model of SI Engine to Detect Misfire Fault

Muhammad Amin Akram*, Muddassar Abbas Rizvi*, Aamer Iqbal Bhatti*, Nadhir Messai **

**Control & Signal Processing Research Group, M. A. Jinnah University, Islamabad, Pakistan.*
***Centre de Recherche en STIC, Université de Reims Champagne Ardenne, UFR Sciences exactes et naturelles, 51689 Reims, France*
E-mail: aminakram@hotmail.com, marizy2k@yahoo.com, aamer987@gmail.com, nadhir.messai@univ-reims.fr

Abstract: Identification of operating mode is a key step in the fault diagnosis of the hybrid systems. The novelty of this paper is the definition of a hybrid observer where discrete event is identified and then continuous model of a sub-system is selected for the design of observer using sliding mode technique. The observer output is finally used for mode identification and fault diagnosis. The proposed method is applied on Spark Ignition (SI) engine for misfire fault detection. The first order sliding mode observer is used to accomplish the task. The mode identification scheme is validated on data generated through hybrid model simulations as well as for data obtained from a 1.3L production vehicle.

Keywords: Mode Identification, Hybrid Systems, SI Engine, Misfire Fault Detection, Hybrid Observer, Sliding Mode Observer, Switched Linear Systems

1. INTRODUCTION

In many engineering systems the states are evolved by an integrated working of continuous and discrete dynamics. Such systems are known as hybrid systems in the literature, having discrete states as modes (Messai *et al.,* 2005; Arogeti *et al.,* 2010; Zhao *et al.,* 2006). In each mode the system behaviour is represented by continuous dynamics corresponding to that mode and discrete event causes the switching between modes. For certain hybrid systems like SI engine, the use of hybrid modelling along with some process information can result in the development of simple methods for estimation and fault diagnosis applications. In this paper we are going to devise one such scheme for the SI engine.

In hybrid models certain physical event causes the system to switch from one mode to another. Mode identification is a major step in the identification and monitoring of hybrid systems (Zhao *et al.,* 2006; Domlan *et al.,* 2007). Recently the problem of mode identification in hybrid systems is being explored actively by the research community (Messai *et al.,* 2005; Arogeti *et al.,* 2010; Zhao *et al.,* 2006; Domlan *et al.,* 2007; Mouchaweh and Messai, 2012; Kouzehgarani, 2010). In (Domlan *et al.,* 2007) the authors applied the model based diagnosis for active mode recognition before state estimation. The method was however applied on academic problem only. The identifications of faults and its effects on state estimation are also not discussed. (Ribot *et al.,* 2009) mentioned that consistency in architecture of health monitoring cannot be achieved without incorporating system knowledge in it. He modelled the three tank system using structural models of systems i.e. individual tanks, pumps and links. Different modes are defined for system nominal behaviour and faulty conditions and diagnosis is carried out using mode identification and consistency checks. The system components are however modelled using algebraic relations instead of modelling system dynamics.

The treatment of potential faults as exogenous inputs for the system and using physically motivated output functions for detecting different faults is found in literature (Aβfalg and Allgower, 2007). The operating mode is related to the healthy system and different faults that can occur in it. An augmented hybrid estimator track possible trajectories involving mode changes before forming the optimization problem for estimating the state. The proposed procedure however has to model many fault conditions and solve multiple differential equations for fault mode identification and augmented state estimation.

Frequent switching that may occur between modes of operations in the hybrid systems result in complex transients (Skaff *et al.,* 2005). The identification of current mode is also a hard task (Messai *et al.,* 2005). The application of model based techniques for hybrid systems is therefore a difficult task due to unpredicted mode changes (Arogeti *et al.,* 2010). In-spite of all the associated difficulties, the approach of using hybrid observer to track system behaviour and using it to evolve a fault diagnostic mechanism is not new (Sabanovick, 2004).

A general survey of SI engine indicates that Mean Value Model (MVM) is the most popular model for parameter estimation using observer design (Butt and Bhatti 2008; Iqbal *et al.,* 2011). Due to averaging nature of this model, it captures less detail of the system and is less complex. Hence it is suitable for many control applications. However the details not captured by the MVM contain information useful for fault diagnosis (Rizvi *et al.,* 2011; Sengupta *et al.,* 2011).

Quite recently hybrid models of SI engine are however evolving for fault diagnosis applications (Rizvi *et al.,* 2011; Sengupta *et al.,* 2011; Rizvi *et al.,* 2012; Rizvi and Bhatti, 2009). These methods used integration of stochastic properties of the model and also used to estimate system states in the presence of measurement and process noise. The potential of application of hybrid model for fault detection applications motivates to represent different modes of system as variable structure and design an observer to estimate the state. This will result in significant simplification as linear model will be used for the estimation of states in all different modes. The states could then be used to identify the active system mode as well.

Sliding mode is one of the main techniques to study the variable structure system (Sabanovick, 2004). Applications of sliding mode observer for fault diagnosis are found in literature (Iqbal *et al.,* 2011; Bhatti *et al.,* 1999; Goh *et al.,* 2002). The technique is however applied mostly to the continuous time linear or nonlinear models and very few references of its application are available for hybrid model applications (Bartolini *et al.,* 2000; Juloski *et al.,* 2007). In present work we have applied sliding mode on engine hybrid model in which healthy and faulty states of system are considered as two different modes and state variables of system are estimated for identifying system modes. The identified modes will then be used to detect misfire fault of SI engine.

Misfire fault is defined as fault due to missing spark, air leakage from cylinder or fault in fuel injection (CARB, 2009). The problem was studied in the past but new methods are still being explored to study the problem (Devasenapati *et al.,* 2010; Malaczynski and VanderPoel, 2010; Rizvi *et al.,* 2009; Bohn *et al.,* 2007; Bohn *et al.,* 2005; Lee *et al.,* 2006; Montini and Speciale, 2006). The methods proposed for the detection of misfire fault include model based techniques, data based techniques and a combination of both model based and data based methods (Rizvi *et al.,* 2011). Model based methods are based on the application of mathematical model of SI engine for the detection of misfire fault. In this regard, (Shiao and Moskwa, 1995) used a nonlinear engine model for torque estimation. He used sliding mode technique to estimate the cylinder pressure. The cylinder pressure is then used to identify the misfire fault in engine. (Bohn *et al.,* 2005) used linearized model for individual harmonics contained in crankshaft speed signal and used Kalman filtering approach to estimate the acceleration and used it to identify the misfire fault in engine. (Sood *et al.,* 1985) developed a mathematical model to estimate the engine torque. He used torque as a variable to identify the misfire fault. The data based methods used artificial neural network, correlation analysis, wavelet transform etc for analysis and identify the misfire fault. (Sood *et al.,* 1985) and (Rizzoni *et al.,* 1988) used correlation based method for misfire fault detection. (Lee *et al.,* 2006) used artificial neural networks for the detection of misfire and (Montini and Speciale, 2006) used wavelet based techniques for detecting misfire faults. Most of the model based and data based techniques used for detecting misfire problem are either computationally very heavy or based on heuristics that lack the physical insight of engine. A comparison of different methods with the method being proposed in this paper is present in later section of this paper.

The basic objective of this paper is to present misfire fault detection technique that is simpler in computation and still provide insight about the real cause of misfire in engine. To ensure the presence of physical insight in method, model based fault detection technique is taken and to maintain the simplicity of computation preference is given to linear model of SI engine along with an observer that is simple but robust enough to absorb model uncertainties. A first order sliding mode observer suits best against these requirements. First order sliding mode is therefore selected for mode identification and mode sequence analysis is used for fault detection.

In this paper, we developed a mode identification scheme for the fault diagnosis of SI engine, using sliding mode observer based on the hybrid model proposed in (Rizvi *et al.,* 2011). Once the convergence of the observer is achieved, it can be used for the fault detection by using the information of the system modes. The method is first simulated by generating the data using proposed model and applying this to the proposed observer. As data is generated using model, all the states are known and the predicted states of model can be verified easily. Later on, the data acquired from an actual engine is fed to the observer and the proposed scheme is validated against this data.

This paper is organized as: Section 2 describes the proposed mode identification scheme for SI engine fault diagnosis. This Section contains subsections that cover hybrid model of SI engine used in this work and the stability analysis of the sliding mode observer for hybrid model. Section 3 discusses the simulation results and Section 4 contains the description of experimental setup and results. Section 5 compares different methods for misfire detection and Section 6 concludes the whole work.

2. THE PROPOSED SCHEME

Consider a switched linear system with q modes represented as:

$$\begin{aligned} \dot{x}(t) &= A_i x(t) + B_i u(t) \\ y(t) &= C_i x(t) \end{aligned} \tag{1}$$

where $x(t) \in R^n$ represents the state vector, $y(t) \in R^p$ represents the output vector, $u(t) \in R^m$ represents the input vector and $\mathrm{i} \in Q \simeq \{1, 2, \ldots, q\}$.

Our proposed scheme uses the fact that if the sequence of occurrence of system modes deviates from that of expected fault free mode sequence then it indicates faulty behaviour of the system (Sengupta *et al.,* 2011). In-case of hybrid systems, two types of faults can be considered: the ones related to the current mode behaviour and the ones affecting the discrete evolution trajectory (Cocquempot *et al.,* 2004). These faults can be diagnosed by monitoring continuous and discrete states separately. However, if continuous states can be translated in terms of modes then a single scheme can be devised to diagnose both types of fault simultaneously. So we extend (1) to include faulty modes as well.

$$\begin{aligned} \dot{x}_f(t) &= \bar{A}_i x_f(t) + \mathrm{B}_i\, u(t) \\ y_f(t) &= C_i x_f(t) \end{aligned} \tag{2}$$

where $i \in \bar{Q} \simeq \{q+1, q+2, ..., 2q\}$ determines the faulty system dynamics among the q possible faulty modes. Now the mode set is

$$\Omega = Q \cup \bar{Q} \tag{3}$$

and for overall system

$$i \in \Omega \tag{4}$$

Next, some terms are defined that will be used in the sequel.

Discretizer Function: When kth mode is active, discretizer function f maps the continuous state of the system to a discrete state j belonging to Ω i.e.

i.e. $j = f_k(x)$ where $j \in \Omega, x \in R$ (5)

A simplest function can be considered to be a comparison of value of x with some pre-defined threshold value.

$$j = f_k(x) = \begin{cases} k+q & \lim\limits_{t\to\infty} \|s - x(t)\| \geq \varepsilon, \quad k \in Q \\ k & \lim\limits_{t\to\infty} \|s - x(t)\| < \varepsilon, \quad k \in Q \\ k & \lim\limits_{t\to\infty} \|s - x(t)\| \geq \varepsilon, \quad k \in \bar{Q} \\ k-q & \lim\limits_{t\to\infty} \|s - x(t)\| < \varepsilon, \quad k \in \bar{Q} \end{cases} \tag{6}$$

where s is a set point and ε is a small number.

Mode Sequence Estimation Function (MSEF): It uses the output of discretizer function and information of active mode i as its arguments and estimates the next mode appearing in the sequence.

$$p = g(j, i),\ p \in \Omega \tag{7}$$

Switching Sequence: Switching sequence S associated with switched systems is indexed by initial state x_0 and is given as:

$$S = x_0;\ (i_0, t_0), (i_1, t_1), ..., (i_{2q}, t_{2q}), ... \tag{8}$$

(Branicky, 1998)

Admissible Set: A non-empty set S_a is said to be admissible set if it contains those switching sequences that result in non-faulty behaviour of (1).

It is clear from the above definition that

$$q \notin s_a,\ \forall q \in \bar{Q}\ \ \forall s_a \in S_a \tag{9}$$

This set can be obtained using system model by generating the expected behaviour of the system and/or using knowledge about system operation.

2.1 Hybrid Model of SI Engine

Before proceeding further, this sub-section explains the hybrid model of SI engine adopted in this work from (Rizvi *et al.,* 2011), along-with the modifications made in this model for our present work. The said model is a switched linear hybrid model developed for a four cylinder engine. Each cylinder is taken as a linear subsystem of the overall system, which actuates sequentially on the corresponding event. At any particular time instant ignition occurs in only one of the four cylinders that provide the power and the other three cylinders (which are in one of the intake, compression or exhaust process) act as a load on this active cylinder. Only power stroke of the cylinders is modelled. When the power stroke of one cylinder is completed it switches to the next subsystem. The switching between subsystems is determined in terms of system states and is a deterministic process. The model represents the steady state behaviour of the system. In steady state the crankshaft speed fluctuations during power stroke are very small. Also due to switching between different subsystems the model validation time is very small, so each subsystem can accurately be represented as a linear time invariant model. The output of the overall system is obtained by the combined effect of all the subsystems.

The hybrid model for a healthy SI engine is defined as a 5-tuple model $<\mu, X, \Gamma, \Sigma, \phi>$ in the literature (Rizvi *et al.,* 2011). The model is however slightly modified to include fault states in it.

$$\Omega = \mu = \mu_H \cup \mu_F \tag{10}$$

where $\mu_H = \{\mu_1, \mu_2, \mu_3, \mu_4\}$ represents the discrete modes corresponding to the four subsystems of the healthy engine and $\mu_F = \{\mu_5, \mu_6, \mu_7, \mu_8\}$ represents the discrete modes corresponding to the four subsystems of the faulty engine.

$X \in R^2$ represents the states of the continuous subsystems. In present case each subsystem contain two states, velocity and acceleration.

$\Gamma = \{G\}$ is a set that contains only a single element for a maximally balanced engine, where G represents mathematical model of all subsystems as state space model. This model is assumed to be linear and stable. The state space model for the subsystems can be computed using literature. In this regard the model derived on the basis of laws of physics can be used (Rizvi *et al.,* 2011). The referenced model proposed a second order system for subsystems of hybrid model of an SI engine. The element of the set Γ contains the equivalent state space representation of the model defined as:

$$\begin{aligned} \dot{x} &= A_i x + Bu \\ y &= Cx \end{aligned} \tag{11}$$

where

$u \in R, A \in R^{2\times 2}, B \in R^{2\times 1}, C \in R^{1\times 2}$, $i = 1,2,3,4$

$\Sigma = \mu \to \mu$ represents the generator function that defines the next transition model. For an IC engine, the piston position has a one to one correspondence with crankshaft position during an ignition cycle. The switching surface is therefore defined in terms of crankshaft position as:

$$For\ \mu_H\ \ \Sigma = \begin{cases} \mu_1 & 4n\pi \le \int \dot{\theta}_1 dt < (4n+1)\pi \\ \mu_2 & (4n+1)\pi \le \int \dot{\theta}_1 dt < (4n+2)\pi \\ \mu_3 & (4n+2)\pi \le \int \dot{\theta}_1 dt < (4n+3)\pi \\ \mu_4 & (4n+3)\pi \le \int \dot{\theta}_1 dt < (4n+4)\pi \end{cases} \tag{12}$$

$$For\ \mu_F\ \ \Sigma = \begin{cases} \mu_5 & 4n\pi \le \int \dot{\theta}_1 dt < (4n+1)\pi \\ \mu_6 & (4n+1)\pi \le \int \dot{\theta}_1 dt < (4n+2)\pi \\ \mu_7 & (4n+2)\pi \le \int \dot{\theta}_1 dt < (4n+3)\pi \\ \mu_8 & (4n+3)\pi \le \int \dot{\theta}_1 dt < (4n+4)\pi \end{cases} \tag{13}$$

where n=0,1,2,3…. and $\int \dot{\theta}_1 dt$ represents the crankshaft speed, which identifies the output of the generator function. Fig. 1 shows the possible mode switching among different subsystems of the SI engine hybrid model.

$\theta : \Gamma \times \mu \times X \times u \to X$ defines the initial condition for the next subsystem after a switching event, where u represents input to the subsystem. The last condition that provides the initial condition to the next subsystem ensures the continuity of response.

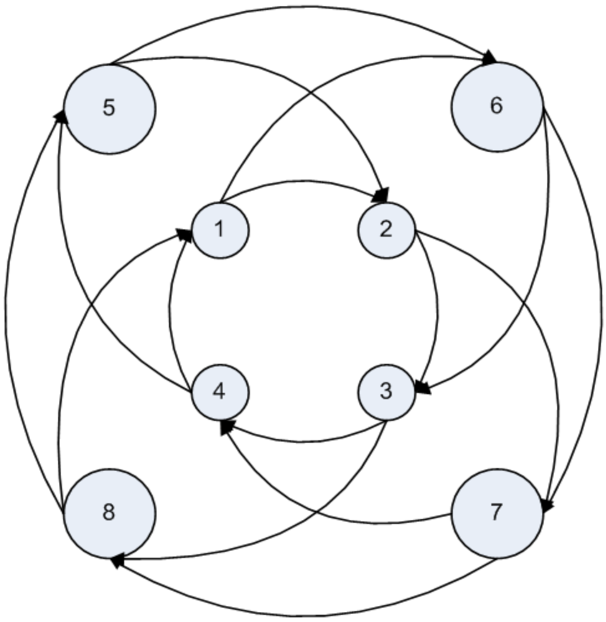

Fig. 1. SI engine modes with switching sequence.

2.2 Mode Identification of SI Engine

Next the proposed mode identification scheme for the fault diagnosis of the SI engine using its hybrid model is described. For any cylinder of SI engine, healthy/faulty modes correspond to the occurrence of the actual production/non-production of the power in the cylinder due to the burning of air fuel mixture. The power is produced if the engine components like igniter, injector and air suction of cylinder are working properly. The assignment of next occurring mode in a sequence observed in healthy and faulty systems to the sets μ_H and μ_F can be established mathematically by (5).

$$\begin{cases} g_i\ AND\ j_i\ AND\ a = 1 \ \Rightarrow \mu_H \\ g_i\ AND\ j_i\ AND\ a = 0 \ \Rightarrow \mu_F \end{cases} \tag{14}$$

where AND represents the logical AND operation and $g_i, j_i\ and\ a$ are equal to 1 for the normal healthy working of the igniter, injector and air/fuel mixture system respectively and 0 for their corresponding faulty operation. The faults considered for this scenario are termed as misfire fault and Section 1 provided literature survey to identify the significance of this fault for SI engine. The system under study can be approximated as a variable structure system with different structure under healthy and faulty conditions. The corresponding healthy and faulty modes are mutually disjoint at any instant. Therefore

$$\mu_H \cap \mu_F = 0 \tag{15}$$

That is, at any time instant the system must be only in one mode; healthy or faulty.

The proposed methodology utilizes the process information along-with its hybrid model and introduces the fault as exogenous input. For the maximally balanced healthy SI engine the switching between subsystems occur sequentially and is a deterministic process. Any deviation of mode sequence is an indication of fault. So for kth mode μ_k, the switching sequence of the modes for the healthy and faulty cases will be as:

$$Fault\ Free\ Case \quad \left.\begin{array}{ll} \mu_k \to \mu_{k+1} & for\ k < 4 \\ \mu_k \to \mu_1 & for\ k = 4 \\ \mu_k \to \mu_{k-3} & for\ 8 > k > 4 \\ \mu_k \to \mu_1 & for\ k = 8 \end{array}\right\} \tag{16}$$

$$Faulty\ Case \quad \left.\begin{array}{ll} \mu_k \to \mu_{k+5} & for\ k < 4 \\ \mu_k \to \mu_5 & for\ k = 4 \\ \mu_k \to \mu_{k+1} & for\ 8 > k > 4 \\ \mu_k \to \mu_5 & for\ k = 8 \end{array}\right\} \tag{17}$$

which implies that

$$\mu_k \in \mu_H \tag{18}$$

or

$$\mu_k \in \mu_F \tag{19}$$

where

$k \in \{1, 2, ..., 8\}$

The mode switching sequence is identified by estimating the continuous state variables of system and identification of active cylinder. Identification of active cylinder can be performed by an analysis of crankshaft position and the identification of continuous state variable of system is physically motivated by the fact that for fault free case, at the start of power stroke the piston is accelerated, under the effects generated by burning of air-fuel mixture inside the cylinder. In the later part of the power cycle the piston starts to decelerate. In case of misfire event, the piston gets no acceleration and continues to decelerate. Large peaks of deceleration are observed in this case (Bohn *et al.,* 2005). We, therefore, use the acceleration as our desired continuous state variable for defining the mode sequence. In production vehicles having SI engine no sensor is provided for the measurement of acceleration data. For this reason, a first order sliding mode observer based on the SI engine hybrid model is designed that uses crankshaft speed to estimate the acceleration. The advantage of using sliding mode observer for state estimation is its inherent property of robustness against uncertainties and disturbances to the system. On account of this property it is possible to estimate the engine states for both healthy and faulty states using same observer. The block diagram of the hybrid observer is shown in Fig. 2. The Fig. 3 describes the complete fault diagnostic methodology. The proposed fault detection method can broadly be categorized as a model based fault detection scheme in which a hybrid model of SI engine is used for state estimation by designing an appropriate observer. Model based fault diagnosis is a well established technique (Isermann, 2005) with very low error rate (Sood *et al.,* 1985). In model based fault detection technique, the mathematical model representing a physical process is connected in parallel to the actual process to generate the residual.

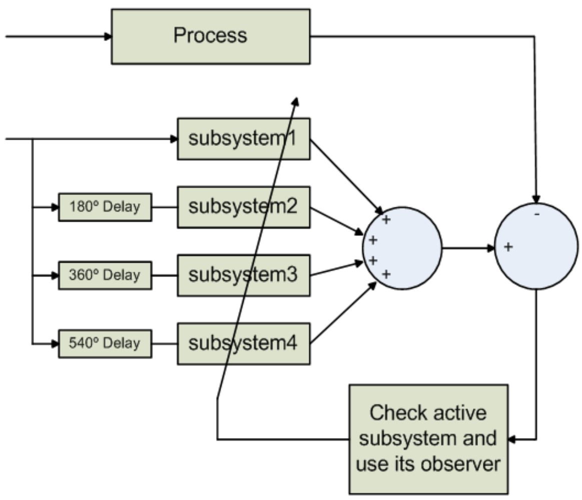

Fig. 2. Structure of hybrid observer.

Each subsystem in Fig. 2 is represented as second order system given below (Rizvi *et al.,* 2011)

$$\begin{aligned} \dot{v}_{i1} &= v_2 \\ \dot{v}_{i2} &= -k_{i2}v_{i2} - k_{i1}v_{i1} + aP \qquad i = 1,2,3,4 \end{aligned} \tag{20}$$

where

v_1 represents the crankshaft velocity

v_2 represents the crankshaft acceleration

a is a constant

P is the power input to the system

Under ideal conditions all the subsystems are assumed to be identical and are working in fault free mode. This ideal behaviour is used as reference to track the states for the SI engine mode identification. Based on the system (20) a first order sliding mode observer is designed to estimate the crankshaft acceleration. For notational simplicity we drop the index i for observer design, so we have

$$\begin{aligned} \dot{\hat{v}}_1 &= \hat{v}_2 \\ \dot{\hat{v}}_2 &= -k_2\hat{v}_2 - k_1\hat{v}_1 + Ksign(e_1) + aP \end{aligned} \tag{21}$$

where

$\hat{v}_1$ represents the estimated velocity of crankshaft

$\hat{v}_2$ represents the estimated acceleration of crankshaft

e_1 represents the speed error

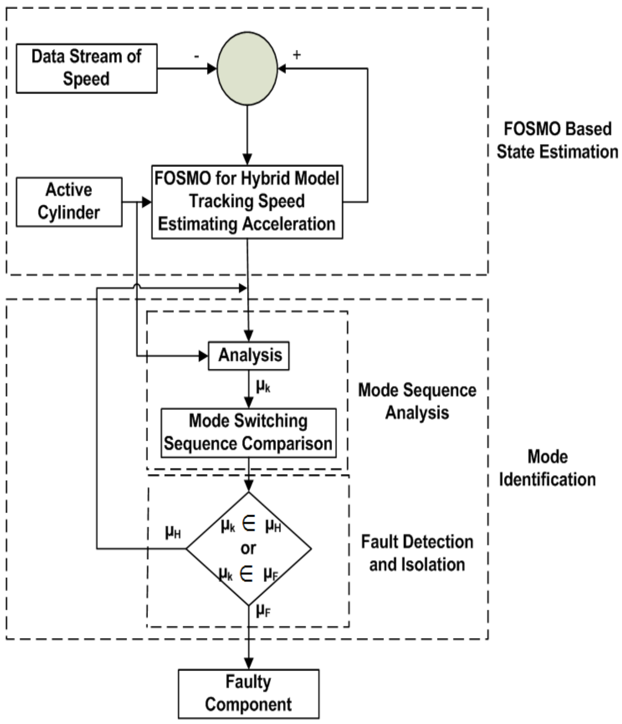

Fig. 3. Proposed methodology for mode identification.

The function sign(.) is defined as:

$$sign(e_1) = \begin{cases} +1 \ \ when \ \ e_1 > 0 \\ -1 \ \ when \ \ e_1 < 0 \end{cases} \tag{22}$$

Using (20) and (21), we get the error dynamics as

$$\begin{aligned} \dot{e}_1 &= e_2 \\ \dot{e}_2 &= -k_2 e_2 - k_1 e_1 + Ksign(e_1) \end{aligned} \tag{23}$$

The stability of the error dynamics ensures that the estimated states converge to the actual system states. In the following the stability analysis of the error dynamics of the SI engine hybrid model is presented.

2.2.1 Stability Analysis

The stability of error dynamics of switching system is determined as given in (Rizvi *et al.,* 2012). For this purpose we consider the error dynamics of each of the sub-systems. Using the assumption of identical subsystems for a maximally balanced system, we can find the characteristics equation for the error dynamics of each subsystem as:

$$s^2 + k_2 s + k_1 = 0 \tag{24}$$

The stability of (24) implies that the error dynamics of each sub-system is stable and a thus a common Lyapunov function can be found for each of the sub-systems. Using the work of (Liberzon, 1999) we find that a switched system is stable for an arbitrary switching sequence if a common Lyapunov function exists for all the sub-systems. So based on the assumption of identical sub-systems the error dynamics of hybrid observer are stable and estimated states would converge to states of the actual system.

3. SIMULATION RESULTS

The above scheme is first validated through simulations. For this purpose, the SI engine hybrid model was initially simulated for fault free case to generate the data for validation of observer. This corresponds to the case $\mu_k \in \mu_H$. The data was then again generated by simulating the model with fault introduced in it to elaborate the faulty case. The values of parameters used for simulation were taken as defined in the literature (Rizvi *et al.,* 2011). The modes were then detected using the proposed algorithm. The mode switching sequence was finally analyzed to identify the presence/absence of fault.

In simulation based method, the hybrid model is simulated and the data of active cylinder identification and crankshaft speed is saved in an array. The cylinder identification is assigned when a pulse input is provided to the sub-system. For first sub-system the cylinder ID is assigned the value 1, for second sub-system the value is 2 and so on. However the data of cylinder ID is plotted in all results after suitable scaling and offset for presenting them on the scale of figures. The crankshaft speed is taken from the model output saved already as an array. A plot of data for the healthy engine and under misfire fault condition is shown in Fig. 4. This data array is then provided as an input to the sliding mode observer to track the engine speed and estimate the engine acceleration (Fig. 3). The results of observer tracking are shown in Fig. 5 for both healthy and faulty cases, from which we can see that observer is tracking the system states quite satisfactorily. The zoomed view of peak of observer tracking response is also shown in Fig. 5 to highlight the unwanted chattering effect present due to the application of first order sliding mode observer. To keep things simple we will carry on with the FOSMO for the present work. Fig. 6 gives the plot of error obtained in observer tracking and Fig. 7 shows the estimated acceleration for both cases mentioned above.

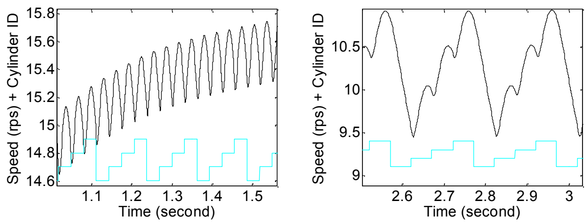

Fig. 4. (Left): Crankshaft speed for fault free case
(Right): Crankshaft speed for misfire fault in cylinder 1.

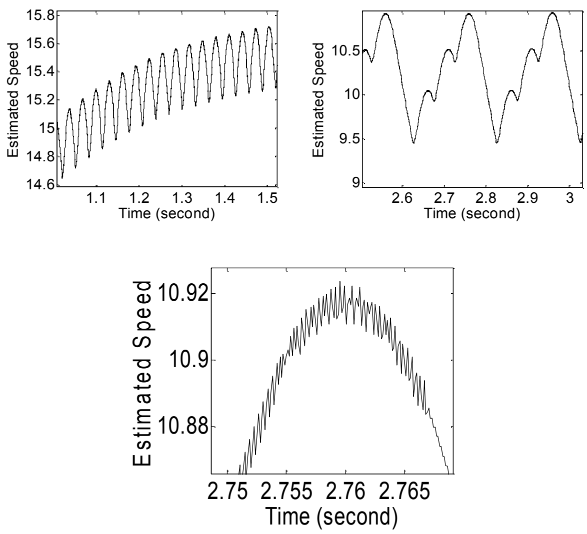

Fig. 5. (Left): Observer tracking for fault free case
(Right): Observer tracking for faulty case
(Bottom): Zoomed view of peak of observer tracking.

The modes are then estimated by the combined analysis of cylinder identification and estimated acceleration. The set of rules for identifying the modes is:

$$\begin{gathered} Cylinder\ ID = k \Rightarrow Mode = k\ or\ k+4 \\ if \\ positive\ peak\ of\ acceleration\ occurs\ for\ kth\ subsystem \\ \Rightarrow Mode = k \\ else \\ Mode = k+4 \end{gathered}$$

Using the above information the monitoring of mode switching sequence is performed according to (16) and (17). So we can see from Fig. 7 that for healthy system the analysis of mode switching sequence results in $\mu_k \in \mu_H$. For misfire fault produced in cylinder 1, we can see from Fig. 7, the occurrence of mode switching sequence becomes as:

$$2 \to 3 \to 4 \to 5 \to 2 \to 3 \to 4 \to 5$$

Instead of

$$2 \to 3 \to 4 \to 1 \to 2 \to 3 \to 4 \to 1$$

That is, the mode switching sequence contains at-least one mode that belongs to μ_F for single misfire event. The absence of mode 1 in the sequence indicates that the first cylinder of SI engine is faulty. Multiple misfires will result in the appearance of more than one members of μ_F within one complete ignition cycle of SI engine, where one ignition cycle of SI engine completes in two revolutions of crankshaft and is equivalent to 720º. The simulation results show how the proposed scheme is used in identifying the active mode and finding the presence/absence of the fault in SI engine hybrid model.

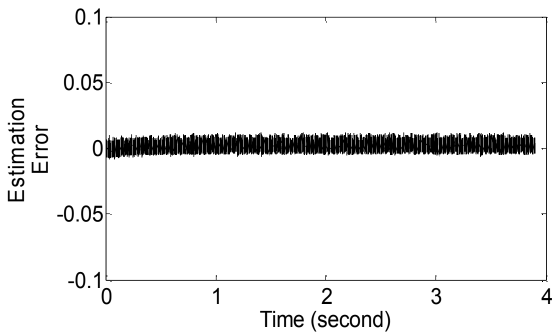

Fig. 6. Estimation error in observer tracking.

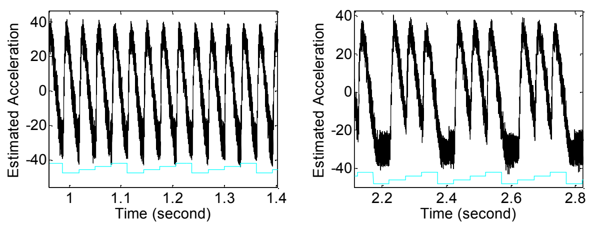

Fig. 7. (Left): Estimated crankshaft acceleration for fault-free case

(Right): Estimated crankshaft acceleration for misfire fault in first cylinder.

4. EXPERIMENTAL RESULTS

This Section describes the experimental setup along-with results used to validate the proposed scheme. Data is acquired from an engine rig of 1.3L production vehicle. In all EFI vehicles, a crankshaft position sensor is always installed in front of a gear assembly. A missing tooth/ double tooth is kept in the gear for identification of reference position. In the testing facility, the gear mounted for monitoring crankshaft position contains 13 teeth so for each complete rotation of shaft only 13 data points can be obtained even if a very high data acquisition rate is selected. This lack of availability of high resolution resulted in the acquisition of noisy signal as compared to the signal generated by simulations.

Moreover, the rig is equipped with wheels and brakes. During experiments the engine throttle is kept at a fixed position and brakes of the rig were controlled manually to maintain the crankshaft speed close to 1000 rpm. For data acquisition the wheels of the rig were raised in air to stop its motion and load was applied on engine through application of brakes. The manual application of load also caused disturbances in the observed data. The working environment of engine is always noisy due to EMI interferences of igniter coils, burning of gases in engine cylinder, engine vibrations and many other factors.

The acquired experimental data was therefore corrupted with low speed disturbances and noise. This noisy signal was fed to the proposed algorithm to establish its ruggedness for practical noisy signals.

To validate the proposed scheme we need crankshaft acceleration but as mentioned earlier the acceleration sensor is not available in the vehicle. So we used FOSMO to estimate the crankshaft acceleration, which requires crankshaft speed as input. During experiments, data from this sensor is acquired using data acquisition card from National Instrument Inc. The data was processed to obtain the crankshaft speed signal. The double tooth provided in the gear assembly of the rig was used to provide the reference and keep track of the cylinder identification. After appropriate filtering this crankshaft speed signal and cylinder identification data is applied to the observer and the crankshaft acceleration is estimated.

Experiment was then repeated with misfire fault introduce in 3rd cylinder. Misfire fault is introduced by inhibiting the igniter signal to engine. The data of engine speed was calculated and saved in an array. Fig. 8 shows the filtered signals of the speed obtained from experimental measurements for fault free case and with misfire fault in third cylinder, and Fig. 9 shows the observer tracking error.

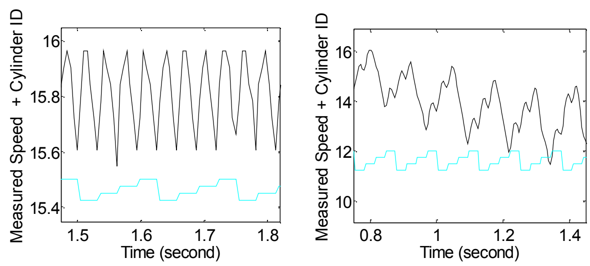

Fig. 8. (Left): Crankshaft speed measurement for fault free case

(Right): Crankshaft speed measurement for misfire fault in cylinder 3.

The estimated acceleration signal along-with cylinder identity is plotted in Fig. 10 for both fault free and faulty cases. The basic trend of simulation results of crankshaft speed and estimated crankshaft acceleration shown in Fig. 4-7 are sufficiently similar to that obtained using the experimental results shown in Fig. 8 and Fig. 10.

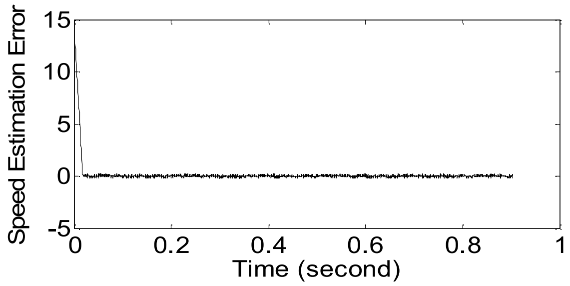

Fig. 9. Observer tracking error.

Using the same procedure described in Section 3, we validated the proposed scheme on this experimental data. The data of estimated acceleration and cylinder identification signal is used for the identification of active mode. The sequence of active mode is stored for further analysis. The analysis of mode switching sequence for this case implies $\mu_k \in \mu_H$. For misfire fault introduced in third cylinder the absence of positive peak in this subsystem results in the presence of one of the modes from μ_F, thus identifying the faulty mode.

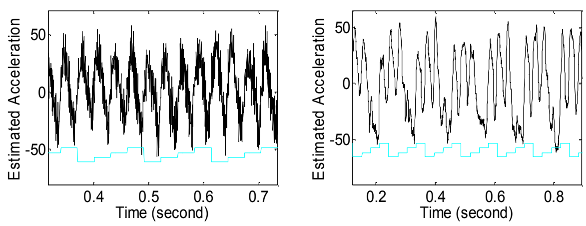

Fig. 10. (Left): Estimated crankshaft acceleration for fault-free case
(Right): Estimated crankshaft acceleration for misfire fault in cylinder 3.

The observed mode sequence is found to be:

$1 \rightarrow 2 \rightarrow 7 \rightarrow 4 \rightarrow 1 \rightarrow 2 \rightarrow 7 \rightarrow 4$

The absence of mode 3 indicates the presence of fault in 3rd cylinder of engine.

Although SI engine is a highly nonlinear system, but its representation using a switched linear hybrid model provides simpler state estimations technique using sliding mode observer. The model also uses a simple way to associate modes with complex non-linear system and demonstrate the application, how mode identification and the allowable mode sequence can be used for fault diagnosis applications.

5. COMPARISON OF METHODS

A brief comparison of the proposed method with some others misfire fault detection methods provided in literature is given in this section. (Sood *et al.,* 1985) has worked on both model based techniques and data based techniques of misfire fault detection. He acknowledged the superiority of model based technique on the basis of error rate. Using his analysis based on the same data set he concluded that the data based technique like cross correlation leads to 18% error rate and model based parameter estimation approach have error rate of 8%. The author in (Sood *et al.,* 1985) used a nonlinear model with time varying parameters in which, he has to solve four differential equations in each iteration. He acknowledged that although the method is more accurate, it is computationally more expensive. He however claimed that the procedure has the advantage of physical reasoning.

Being model based method, the proposed method shares the advantage of physical reasoning with (Sood *et al.,* 1985) method. However the proposed method is based on the state estimation using linear model which is easier to analyze.

(Shiao and Moskwa, 1995) used model based approach and first order sliding mode to estimate cylinder pressure for identifying faulty cylinder. He identified that use of nonlinear sliding observer based on measurements of engine speed provides an accurate, low cost and reliable way to acquire desired states. The model used by (Shiao and Moskwa, 1995) was nonlinear in which the observer lose its observability at Top Dead Centre (TDC) of cylinder being analyzed.

Being using first order sliding mode technique based on the measurement of engine speed, the proposed method shares the simplicity of (Shiao and Moskwa, 1995) method but is simpler on account of linear model.

(Bohn *et al.,* 2005) has used linear models to estimate the acceleration using Kalman filters. The estimation using Kalman filters not only need more computation but also need noise covariance matrices Q and R which are difficult to estimate.

In comparison to the data based methods, the proposed method has advantage of being supported by physical reasoning. Also most data based techniques are sensitive to factors like engine speed (Sood *et al.,* 1985). As an example if correlation analysis is used to compare some recorded signal of faulty engine speed, then it is necessary that engine be operated at the same speed at which the fault signatures were taken. For identifying different fault categories like fault in different cylinders or double misfire, the observed signals have to be compared with multiple number of signature signals. (Rizzoni *et al.,* 1988) has adopted similar methodology for identification of misfiring cylinder. When engine is not operating at speed at which fault signatures were taken, the two signals will have different frequencies that cannot be compared easily. One solution is to take fault signatures at a large number of different speeds. This approach will however increase the computational requirement to make it infeasible.

6. CONCLUSION

This paper presented the mode identification of the SI engine in which modes correspond to operation of different sub-systems of SI engine. In the proposed methodology the identification of system states was physically motivated and a first order sliding mode observer was used for their estimation. The proposed scheme is validated both through the simulations and experimental results. The data for experimental verification was acquired from a 1.3L production vehicle under steady state conditions and was noisy. The correct detection of fault in the presence of noisy data is a clear indication of robustness of proposed algorithm for misfire fault detection. The chattering observed in the estimated state needs attention and authors are currently working to suppress it by using appropriate technique.

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