Mode Identification Based Fault Diagnosis of Hybrid Systems

By

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Dedicated to
My Family and Teachers

TABLE OF CONTENTS

CHAPTER 3

LIST OF FIGURES

LIST OF ACRONYMS

ARR	Analytical Redundancy Relations
BDC	Bottom Dead Center
CLF	Common Lyapunov Function
DFA	Deterministic Finite Automata
ECU	Electronic Control Unit
EKF	Extended Kalman Filter
FDI	Fault Detection and Isolation
FOSMO	First Order Sliding Mode Observer
FSM	Finite State Machine
GUAS	Global Uniform Asymptotic Stable
HBG	Hybrid Bond Graph
HOSM	High Order Sliding Mode
HOSMO	High Order Sliding Mode Observer
IFAC	International Federation of Automatic Control
LTI	Linear Time Invariant
MLF	Multiple Lyapunov Function
MVEM	Mean Value Engine Model
OBD-II	On-Board Diagnostic-II
SI	Spark Ignition
SLS	Switched Linear System
SMC	Sliding Mode Control
SMO	Sliding Mode Observer
TDC	Top Dead Centre
UIEKF	Unknown Input Extended Kalman Filter
VSC	Variable Structure Control

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ABSTRACT

With technological advancements, modern engineering systems are improving in terms of performance, size and cost but at the expense of complexity; making their analysis and control extremely difficult. A fundamental issue regarding these systems is to ensure their safety and reliability due to their vulnerability to faults; owing to their complexity. The situation becomes even worse as the corresponding fault diagnosis algorithms are also becoming more complex and computationally expensive for the online implementation. The problem at hand is to design a simple, reliable and easy to implement fault detection and isolation scheme for these systems. One approach to design such a fault detection scheme for these complex engineering systems is to partition the system into simpler interacting subsystems and designing the desired fault diagnosis scheme for these simpler subsystems. Hybrid modeling provides us a platform to represent these complex engineering systems in simpler subsystems working collectively. Hybrid systems are those having both continuous and discrete dynamics. In these systems, discrete states are known as modes and switching between modes occurs on discrete events. In our proposed scheme, healthy and faulty modes are defined by estimating and analyzing continuous states of the system. This process of state estimation is performed by using Sliding Mode Observers (SMO). The monitoring of system modes is performed by designing a Deterministic Finite Automaton (DFA) that uses modes of the hybrid systems represented as symbols of a language, at its input. The proposed scheme is validated both through simulations and experimental data. Data for the experimental validation of the proposed scheme is acquired from an engine rig of a 1.3L production vehicle compliant with the On-Board Diagnostic II (OBD-II). Proposed scheme is easy to implement on account of being model-based. Instead of Kalman filter, SMO is used for the state estimation that is computationally cheaper. In general, there are two types of faults in hybrid systems; ones related to the current mode behavior and the others affecting the discrete evolution trajectory. In our design, we have detected both these faults using a single scheme by identifying and monitoring system modes. Moreover, detection and isolation of new faults can be easily accommodated by introducing new mode sequences in a fault set.

LIST OF PUBLICATIONS

Journal Publications

1. **Muhammad Amin Akram,** Muddassar Abbas Rizvi, Aamer Iqbal Bhatti and Nadhir Messai, "Mode Identification for Hybrid Model of SI Engine to Detect Misfire Fault" *Journal of Control Engineering and Applied Informatics*, Vol. 16, No. 3, pp: 65-74, 2014. **[Impact Factor: 0.449]**

Conference Publications

1. Rizvi MA, Zaidi SH, **Akram MA** and Bhatti AI, "Misfire Fault Detection in SI Engine Using Sliding Mode Observer" *In: IECON 2012- 38th Annual Conference on IEEE Industrial Electronics Society*; 25-28 October 2012; Montreal, Canada. pp. 5114-5119
2. **Muhammad Amin Akram,** Aamer Iqbal Bhatti and Qadeer Ahmed, "Air/fuel ratio estimation of SI engine using higher order sliding mode" *IFAC-AAC 2013*, Tokyo, Japan

CHAPTER 1

INTRODUCTION

Modern engineering systems are complex in nature. This complexity arises from the recent technological advancements that involve interaction of various technical domains for the proper functionality of these systems. Due to their inherent complexity, these systems are more prone to fault and thus have reliability issues. Fault diagnosis is an efficient way to address this problem and to meet the reliability requirement. There is an increasing demand for monitoring of these engineering systems to ensure their fault-free, reliable and safe operation. However, due to the increased complexity of modern engineering systems, corresponding fault diagnosis algorithms are also becoming more complex and computationally expensive for online implementation. There is always a quest for developing simple, reliable, efficient and easy-to-implement fault diagnosis techniques for these complex engineering systems. One approach to achieve this task is to partition the system into simpler interacting subsystems and design the required fault diagnosis scheme for these simpler subsystems. However, such partitioning of a large complex system is not an easy task. This can be facilitated by using hybrid modeling of the system that can be used to represent these complex engineering systems in simpler subsystems working collectively to complete a required job. Many engineering systems that work by the interaction of multiple subsystems can more easily be modeled as hybrid systems, with simpler subsystem models that interact with each other periodically at discrete events to generate the output. The discrete states in the hybrid systems correspond to the system modes and in each mode system dynamics are governed by the corresponding continuous dynamics. In hybrid systems, the states evolve by switching between various operating modes based on system states, time or some external event.

Representation of real-world complex systems by hybrid models simplifies analysis and controller design process for these systems by considering simpler subsystems instead of a large complex system. Furthermore, system performance can be improved to a significant extent by designing high performance control systems by switching between simpler systems. Figure-1.1 shows an example of representing a real-world system by a hybrid model. The system presented in this figure represents a temperature regulation system in a house. This system operates in two modes: “on” and “off”. The switching between these modes occurs based on the system’s continuous state. If the temperature becomes greater than a threshold value determined by the desired temperature then the system switches to the “off” mode and for temperature less than a minimum value determined by the desired temperature it switches to the “on” mode. In each mode, the evolution of the temperature is governed by a differential equation.

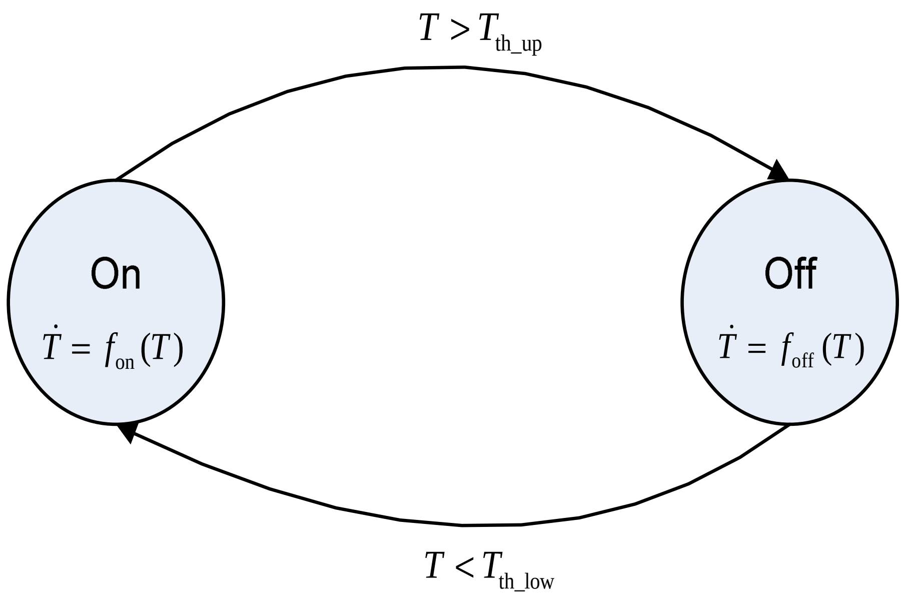

Figure-1.1 Temperature control system

This dissertation proposes simple, reliable and easy-to-implement, novel Fault Detection and Isolation (FDI) scheme based on the analysis of the identified modes, for a class of hybrid systems. In the current chapter, we cover motivation and objectives of the presented work. The contributions of this work and thesis outlines are given subsequently.

1.1 Motivation

Due to the recent technological advancements, modern engineering systems are improving in terms of functionality, performance, reliability, size and cost. These improvements, however, come at the expense of complexity. Nowadays, state-of-the-art systems are designed in multidisciplinary fashion, where various technical domains, such as hardware and software, interact with each other to complete a certain task. On one hand, this interactive design ameliorates the performance and functionality of the systems, whereas, on the other hand, it manifolds their complexity. Consequently, modern engineering systems are more prone to faults and also the algorithms for the detection of faults in these systems become more complex. Therefore, the researchers strive for simpler, effective and more reliable FDI schemes for these systems. Many complex engineering systems are inherently designed in such a way that they operate by periodic repetition of certain operation of their subsystems. These systems can more accurately be represented by hybrid models. In hybrid modeling, a complex engineering system is represented by partitioning it into smaller and simpler interacting subsystems thus assisting in developing a simple and reliable FDI scheme by considering these simpler subsystems instead of the complex system itself.

As mentioned above, in modern engineering systems the increased complexity has also enhanced the probability of fault occurrence. Lack of the ability of in-time fault detection can cause financial as well as life losses. Few examples in this regard are given below:

- On 25th May 1979, American Airline DC 10 crashed at Chicago O'Hare International Airport, causing 273 deaths. The pilot did not get timely indication of the fault. Later investigations showed that the crash could have been avoided [1].
- In 1986, a famous incident of the nuclear meltdown occurred at Chernobyl, Russia. This disaster was declared as the worst nuclear power plant accident in the history of nuclear power engineering; both in terms of finances and human casualties. In the later investigative studies, it was revealed that the faulty and

obsolete technology and an absence of fault-handling mechanisms were mainly responsible for the calamity [2].

- The Ariane 5 launcher was destroyed on 4th June 1996 by entering in self-destruction mode 37 seconds after takeoff. Investigations revealed that the major cause of the disaster was an error in software, which was originally copied from Ariane 4. Apparently, it worked perfectly well on Ariane 4, but was not compatible with Ariane 5 due to its changed continuous dynamical system [3].

FDI of a process can be performed by using hardware or analytical redundancy methods. In case of hardware redundancy, additional components are used along with the already available components in the system. The major advantages provided by this approach are enhanced reliability and direct isolation of the fault. However along with these advantages, requirement of additional hardware associates few disadvantages with this approach like increase in the cost, weight and size. In case of analytical redundancy, the process model is executed in parallel with the actual process, and then the results are compared for the FDI of the process. The primary advantage of this method is low hardware cost, small size and lesser weight. Due to these advantages, analytical redundancy based FDI methods are becoming more popular. Among various available analytical redundancy based FDI techniques, analytical model-based technique requires the deepest knowledge of the process and thus is the most efficient approach for FDI [4], [5]. However, traditional model-based methods of FDI cannot be directly applied to the hybrid systems due to several reasons. Firstly, in hybrid systems, monitoring the threshold crossing by the residual may not necessarily be an indication of a fault but it can be due to the mismatched modes as mentioned in [6]. Thus, first of all we have to identify the operating mode from various modes of hybrid system, known as mode identification and, therefore, is a key step and natural way in the identification and monitoring of hybrid systems [7], [8]. However, the identification of current mode is a hard task [9]. In the last decade or so, the problem of mode identification in hybrid systems is being explored actively by the research community [6], [7], [8], [9], [10], [11]. Secondly, for monitoring of hybrid systems, mode occurrence sequence may also be considered in addition to the observation of residual signal. In the literature, we find that the deviation of mode occurrence sequence from that of expected can be used for fault detection in hybrid systems [12].

Standard FDI literature for linear systems gives several approaches for fault detection and isolation, one of which is based on state estimation [13]. For the health monitoring of the hybrid systems, simpler methods can be evolved by identifying the active mode and testing mode sequence along with the analysis of system continuous states. This requirement corresponds to the state estimation based fault detection of dynamic systems with some additional work load to develop a generalized fault detection scheme. System states can be estimated more easily for simple subsystems by utilizing robust methods like sliding mode technique, which provides reliable estimate of states even on the switching instants.

In many applications of the control systems, *a prior* availability of system states is assumed. This assumption can be invalid for some situations. In such cases we have to estimate system states using an observer. Sliding Mode Observer (SMO) is an observer based on the concepts of sliding mode control (see Section 2.4) and used for robust estimation of states and parameters, which can be further utilized in the system monitoring and fault diagnosis applications. SMOs are in use for many years by the control community for parameter/state estimation and fault diagnosis [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24]. The wide use of sliding mode technique in such applications is due to its finite time convergence and robustness properties [25]. Moreover, in contrast to traditional estimation approaches that are mostly for linear systems and thus are useful in only a specific operating region, SMO is a nonlinear technique that is equally applicable to linear as well as nonlinear systems directly without requiring the linearization of system around the operating point. The major part of the literature regarding application of sliding mode technique is for the continuous time linear or nonlinear models. However this trend is now also shifting towards hybrid systems and many recent works containing application of SMO to hybrid systems can be found in the literature [26], [27], [28], [29], [30], [31]. In case of hybrid systems, the FDI algorithm should be robust enough to cope with model uncertainties and the discontinuities at the switching instants. Sliding mode technique is a suitable candidate for these requirements due to its aforementioned properties. Sliding mode approach has been adopted by many authors for the estimation of continuous and discrete states for various classes of hybrid systems [26], [27], [28], [29], [30], [31], [32], [33], [34]. These robust state estimates can be further used for fault diagnosis of hybrid systems.

Two active communities working in hybrid systems are control system community and computer science community. They both approximate these systems according to their relevant disciplines, in continuous and discrete systems respectively [3], [35]. The computer science community focuses on the discrete behavior of the system and puts less emphasis on the continuous dynamics. On the other hand, the control system researchers emphasize on the continuous dynamics and take hybrid systems as continuous systems with switching. Both of these communities use different tools from corresponding disciplines according to their domains of applications. These both approaches have their own advantages and disadvantages e.g. system model used in model-based approach is just an approximation of the actual system and has uncertainties. This can be tackled by using more accurate and detailed model of the system but it will increase the complexity of the algorithm. Similarly data-based methods lack the details of physical link of the algorithm. Integration of methods from these two communities empowers us to use the advantages of both disciplines depending upon the applications. In the literature many authors adopted this integrated approach and claimed more accuracy and better performance in their proposed methods [36], [37], [38].

1.2 Objectives

The aim of this thesis is designing a simple, easy-to-implement, efficient, and robust FDI scheme for an important class of hybrid systems, namely, Switched Linear Systems (SLS). These are the systems in which each subsystem is represented by the Linear Time Invariant (LTI) system [39]. The study of SLS has its importance in that they can be used to model many complex engineering systems. This enables us to handle these complex engineering systems with ease since many powerful tools can be used for the analysis of SLS from the well established theory of the linear systems. This approach of analyzing these systems bridges the gap between linear and complex systems. Due to these important features of SLS they are becoming more popular in the control community.

1.3 Contributions

The proposed scheme utilizes system model and therefore, it can be categorized under model-based fault detection schemes. Model-based FDI techniques are easy to implement and need no extra hardware and space as required by the hardware redundancy based schemes. The system states analyzed for the FDI purpose are estimated by the SMO that provides robust estimate even in the presence of model uncertainties and discontinuities on the switching instants. Generally Kalman filter is adopted for the state estimation but it requires many online computations for its operation. SMO is a non recursive technique and thus is computationally economical than Kalman filter. The computational complexity of Extended Kalman Filter (EKF) is $O(N^3)$ while that of SMO is $O(N)$ for a system of order N [40]. For this reason SMO is a better choice for the online implementation and is adopted in this work for state estimation.

The main contributions of the thesis are summarized as:

Mode identification scheme for the FDI of SLS

A mode identification scheme is proposed for the FDI of an important class of hybrid systems known as Switched Linear Systems (SLS). System states are estimated using a stack of SMO and are analyzed to identify modes that are monitored for the FDI purpose. Detection and isolation of new faults can be easily made by introducing corresponding mode sequences in a set, called as fault set.

Mode identification scheme for the FDI of SLS with identical subsystems

A mode identification scheme is proposed for the FDI of SLS having identical subsystems. The previously used SMO stack cannot be adopted for such systems, so it is enhanced for these systems by utilizing additional stacks of SMO. The proposed scheme is successfully applied to the Spark Ignition (SI) engine having identical subsystems. The application of the proposed FDI scheme on the SI engine provides an easy to implement technique involving simpler computations and still provides physical insight about the detected fault.

Deterministic Finite Automaton (DFA) design for the FDI of SLS

A Deterministic Finite Automaton (DFA) design is proposed to be used in the FDI of the SLS. The proposed DFA takes the identified modes, represented as the symbol of a language acceptable to the DFA, as the input. In the hybrid systems, two types of fault can be considered. The use of the proposed DFA in the FDI of hybrid systems enables us to diagnose these both types of fault simultaneously and using the same DFA structure.

Mode identification scheme for the misfire detection in the SI engine

The use of the mode sequence monitoring in the FDI process is demonstrated through misfire fault detection in the SI engine. A mode identification scheme is proposed for the detection of misfire fault in the SI engine. The engine setup used to acquire experimental data is a 1.3L spark ignition engine with four cylinders. A hybrid observer is defined based on the hybrid model of the SI engine, where discrete event is identified to select the continuous model of a subsystem for the design of observer using sliding mode technique. The observer output is finally utilized in mode identification and fault diagnosis.

1.4 Thesis Overview

The remainder of the thesis is organized as follows:

Chapter 2 provides the necessary background for the forthcoming chapters. It basically consists of two main parts: the first one is about the hybrid systems and its relevant terminology and the second part is about the sliding mode technique.

This first part of this chapter covers some key concepts related to the hybrid systems. An important class of hybrid systems, known as switched systems, is discussed. After this, different types of switching are explained. The stability of hybrid systems is an important issue as it depends on the system dynamics as well as on the switching sequence. Two important tools regarding stability of hybrid systems are also described.

The second part of the Chapter 2 covers the basic concepts and terminology related to the Sliding Mode Control (SMC). This mainly includes the design process of the SMC, properties of SMC and SMOs.

Chapter 3 gives the basic FDI terminologies and covers different approaches used in the literature for this purpose. This chapter covers the state of the art FDI techniques for the linear, nonlinear and hybrid systems along with their advantages and disadvantages. This chapter also highlights the key features and benefits of the technique proposed in this dissertation in comparison with the existing techniques.

Chapter 4 presents a mode identification scheme for an important class of hybrid systems known as Switched Linear Systems. This chapter introduces the DFA design and its use in the FDI of the SLS. The proposed algorithm is illustrated through a simulation example by applying it to a switched linear model.

Chapter 5 enhances the mode identification scheme of Chapter 4 to the SLSs with identical systems as well. This chapter also presents the experimental setup used in this thesis for data acquisition. The proposed algorithm is applied to a switched linear model of the SI engine and the results for simulations and experimental data are presented.

Chapter 6 presents the use of mode sequence monitoring in the FDI by the detection of the misfire fault in the SI engine. This chapter starts with an introduction to the misfire fault. After this hybrid model of SI engine is presented and the details of the proposed scheme is described. The proposed misfire detection and isolation scheme is validated through simulations and experimental data and the results are presented in this chapter. Finally a comparison of the existing misfire detection approaches and the proposed approach is presented.

Chapter 7 concludes the dissertation and also provides some tasks related to the presented work that can be performed in future.

CHAPTER 2

PRELIMINARIES

As the work presented in this dissertation is related to the FDI of the hybrid systems, so this chapter is written to provide the essential background for the rest of the material. The FDI concepts and related work, in general as well as for the hybrid systems, are given in the next chapter.

This chapter mainly consists of two parts. The first three Sections discuss hybrid systems. Hybrid systems have recently gained a lot of attention of the research community as they can be used to model the interaction between the continuous and the discrete dynamics in the modern engineering systems. We introduce hybrid systems and its related terminology in Section 2.1. In Section 2.2, we discuss an important class of hybrid systems, known as switched systems. It also contains discussion on the various types of switching. In Section 2.3, we discuss the stability of such systems, which has an important role in the study of hybrid systems as the stability of these systems depends on the individual subsystems as well as on the switching signals.

As described in Chapter 1, we are using sliding mode technique for the state estimation of hybrid systems so the last two Sections are added to provide a flavor of this technique. In Section 2.4, we introduce the concepts of SMC. Subsequently, we discuss SMO in Section 2.5. We'll mainly cover topics related to the design process of SMC as well as SMO and their benefits and drawbacks. Finally, we conclude this chapter in Section 2.6.

2.1 Introduction to hybrid systems

Hybrid systems have both continuous and discrete dynamics. The discrete states correspond to system modes and in each mode system dynamics are represented by corresponding dynamics usually described by differential or difference equations. The states of the hybrid system evolve by switching between various operating modes that occur based on system states, time or some external event. Many real-world systems can be represented by hybrid models. Few examples of hybrid systems include automotives, air traffic control, robot manipulators, diode, analog to digital converters, copier, automated highways, gear transmission, bouncing ball etc [3], [41].

Mathematically, hybrid systems can be represented by using set tuple notation $< X, X_0, u, \rightarrow, Y, H >$ [42]

where

X represents the states

X_0 is the set of initial states

u represents the inputs

$\rightarrow$ represent transition relations

Y represents the output

H represents the transfer function of the system.

In [41], different modeling techniques for the hybrid systems are described. The diverse nature of modeling techniques available for the hybrid systems is due to contributions from different communities working in these systems. As discussed in Chapter 1, the computer science community focuses on the discrete behavior of the system and puts less stress on the continuous dynamics. The main issues considered by the computer science community are well-posedness, simulation and verification. On the other hand, the control systems researchers emphasize on the continuous dynamics and take hybrid systems as the continuous systems with switching, generally known as switched systems [43]. The main issues studied by the control system researchers are stability analysis and control synthesis.

2.2 Switched systems

The switched systems can be viewed as an abstraction of the hybrid systems; they can be obtained by taking into account all possible switching patterns, and neglecting the details of discrete dynamics. Mathematically we can represent switched systems as follows [39]:

$$\begin{aligned} \dot{x}(t) &= f_\sigma(x(t), u(t), d(t)) \qquad x(t_0) = x_0 \\ y(t) &= g_\sigma(x(t), w(t)) \end{aligned} \tag{2.1}$$

where

$x(t)$ is the state vector

$u(t)$ is the controlled input vector

$y(t)$ is the measured output vector

$d(t), w(t)$ are the external signals like perturbations

f_k and $g_k, k \in M$ are vector functions

σ is the piecewise constant signal, denoting switching signal, taking value from an index set $M \overset{def}{=} \{1, 2, ..., m\}$. Switching signal can be a function of time, state, output, its own past value and external signal.

The individual constituent model, given as follows, is known as **mode** of the switched system.

$$\begin{aligned} \dot{x}(t) &= f_k(x(t), u(t), d(t)) \\ y(t) &= g_k(x(t), w(t)) \qquad , k \in M \end{aligned} \tag{2.2}$$

A switching device usually known as supervisor produces the switching signal σ to control the switching between modes.

2.2.1 Types of switching

In switched systems, switching mechanism has a crucial role. Its importance can be seen as the stability of these systems is also affected by the switching pattern. There are several types of switching that can exist in a switched system. In [43], the switching events are classified as follows:

- State dependent switching
- Time dependent switching
- Autonomous switching
- Controlled switching

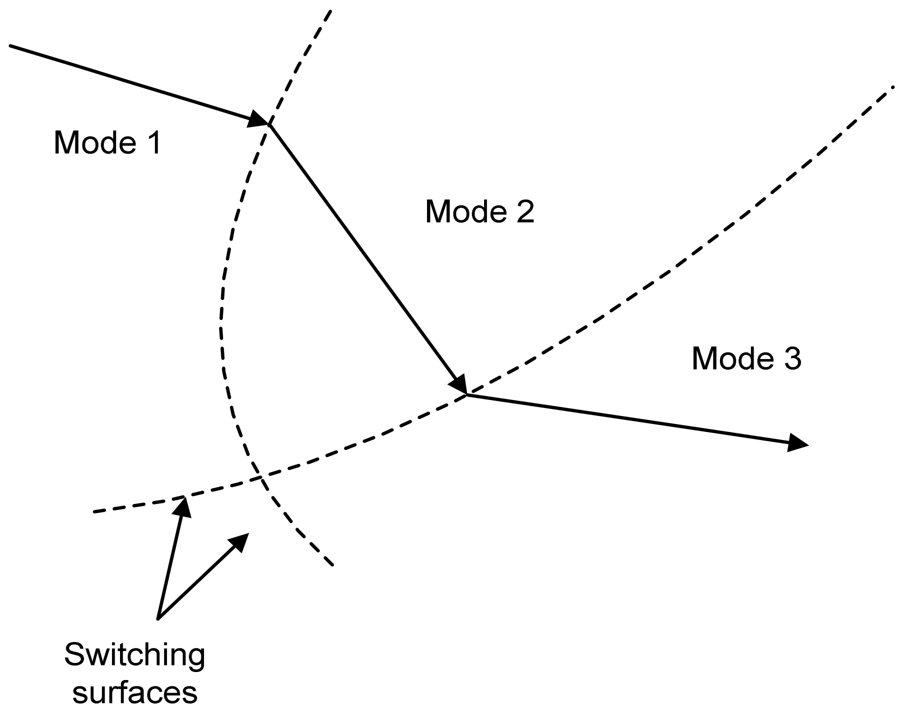

Figure-2.1 State dependent switching

2.2.1.1 State dependent switching

In this type of switching, system switches from one mode to another depending upon the continuous state of the system. This can be understood by considering a continuous state space that is partitioned into several operating regions (finite or infinite in number) by the switching surfaces. Each operating region is assigned a continuous time system. When system trajectory strikes a switching surface it jumps to a new state value given by a reset map, as depicted in Figure-2.1. In this figure, the dotted lines indicate the switching surfaces and the lines with arrow heads indicate the continuous part of the trajectory.

2.2.1.2 Time dependent switching

Consider a family of systems given as

$$\dot{x} = f_i(x), i \in M \tag{2.3}$$

The function f_i is assumed to be Lipschitz.

We use the notion of switching signal $\sigma : [0, \infty) \to M$ to define a switched system by family of systems represented by (2.3). The function $\sigma : [0, \infty) \to M$ has finite number of discontinuities called switching times and has a constant value between two consecutive switching times. Therefore, we define a time dependent switched system as:

$$\dot{x}(t) = f_{\sigma}(t)(x(t)) \tag{2.4}$$

2.2.1.3 Autonomous switching

In autonomous switching, we have no control on the switching mechanism. The state dependent switching described above belongs to this type of switching. Time dependent switching is said to belong to this category when the rule defining the switching signal is not known.

2.2.1.4 Controlled switching

In this case, the switching can be controlled by the designer to obtain the desired task from the system. Controlled switching can also be state or time dependent e.g. in case of automotives, manual transmission corresponds to the controlled state dependent switching.

To understand these switching types, we can take the example from automotive industry in which manual gear transmission corresponds to the controlled state dependent switching whereas automatic transmission corresponds to the autonomous state dependent switching. Manual transmission can also be time dependent in case of parallel parking [43].

2.2.2 Switched Linear Systems

Switched Linear Systems are an important class of the hybrid systems consisting of several LTI systems and a rule for coordinating switching between these LTI systems. They can be represented as follows [39]:

$$\dot{x}(t) = A_{\sigma}(x(t)) \tag{2.5}$$

where σ is the piecewise constant signal defined earlier.

The study of SLS is important as they can be used to model many complex engineering systems. This enables us to handle these complex systems with ease since many powerful tools can be used for the analysis of switched linear systems from the well established theory of linear systems. This approach of analyzing the complex engineering systems bridges the gap between the linear systems and these complex systems. Due to these important features of switched linear systems they are becoming more popular in the control community.

As an example, we take the switched linear model of four cylinder engine in which each cylinder is taken as a linear subsystem of the overall system. At a particular time instant, ignition occurs in only one cylinder. The said model uses only the power stroke of the cylinders. After completion of the power stroke of active cylinder, it switches to the next subsystem. The switching between subsystems occurs based on system states and is a deterministic process. The detailed description of model is given in Chapter 5.

2.3 Stability of the hybrid systems

The stability of the hybrid systems has been studied by many authors and various approaches for the stability analysis of switched systems can be found in the literature [41], [43], [44], [45], [46], [47], [48]. Unlike the conventional dynamic systems, the stability of the switched systems depends on the switching signal as well. It is possible to have all the stable subsystems in a switched system but still the overall system becomes unstable depending upon the switching signal. Such a scenario can be witnessed in the following example taken from [45].

$$\dot{x}(t) = \begin{cases} A_1 x & \text{if } x_1 x_2 < 0 \\ A_2 x & \text{if } x_1 x_2 > 0 \end{cases}$$
$$\text{with} \tag{2.6}$$
$$A_1 = \begin{bmatrix} -1 & 10 \\ -100 & -1 \end{bmatrix}, A_2 = \begin{bmatrix} -1 & 100 \\ -10 & -1 \end{bmatrix}$$

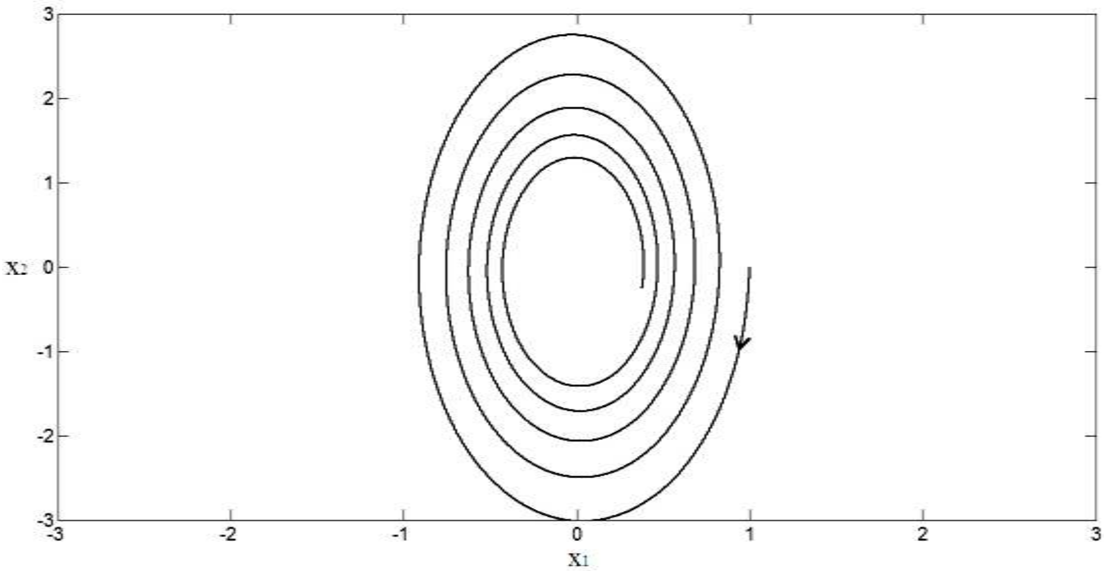

Figure-2.2 Phase portrait of A_1 [45]

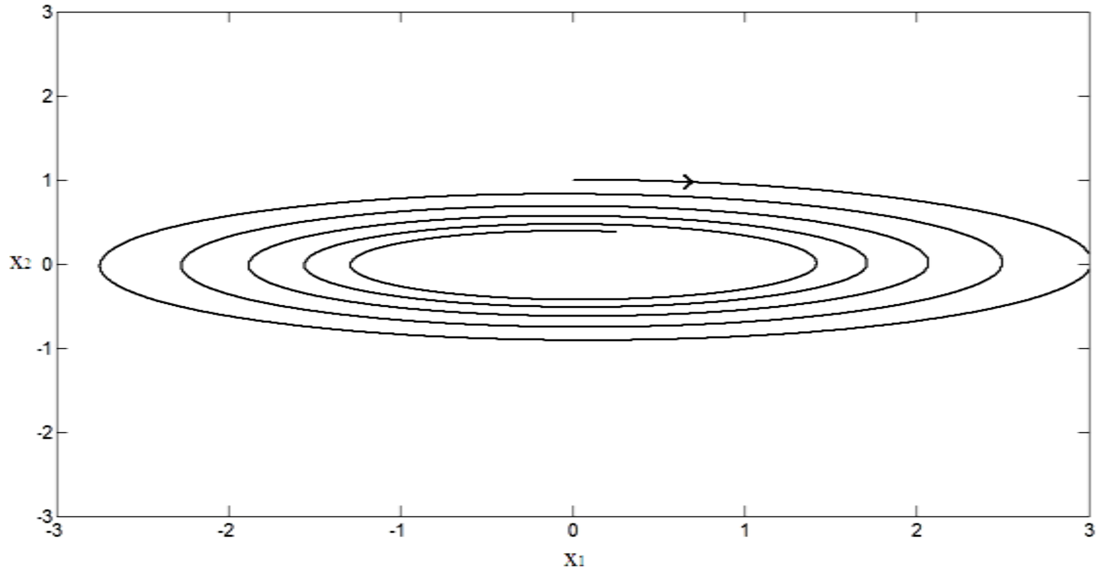

Figure-2.3 Phase portrait A_2 [45]

Eigen values of both A_1 and A_2 are found to be -1.0000+31.6228i, -1.0000 -31.6228i, which means that both the subsystems are individually stable. This is depicted by the phase portraits of individual subsystems in Figure-2.2 and Figure-2.3 respectively.

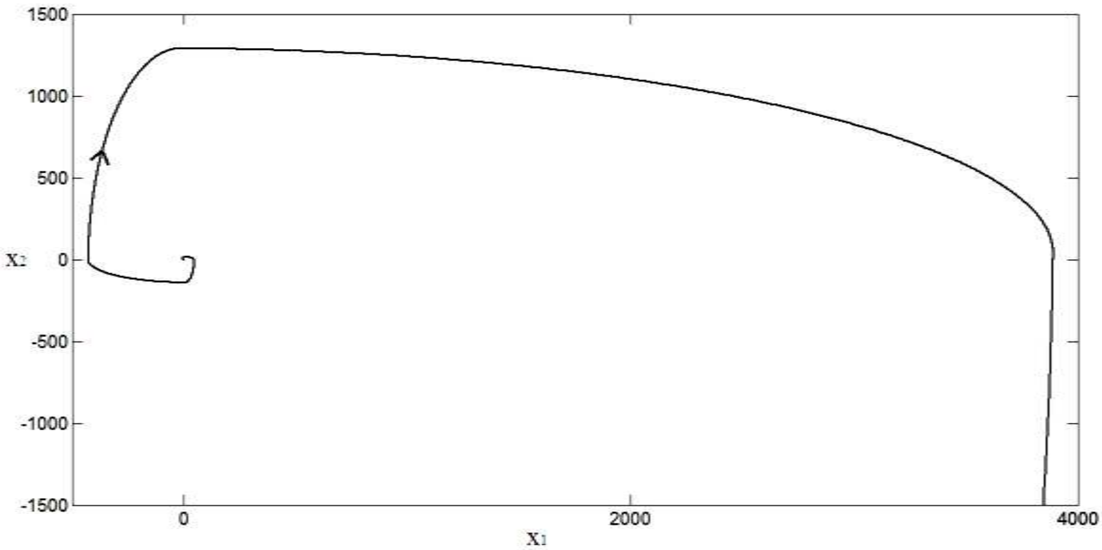

Figure-2.4 Phase portrait of switched system [45]

For switching conditions given in (2.6), we find that the given switched system becomes unstable even though the individual subsystems are stable. The phase portrait of overall switched system confirming this result is given in the Figure-2.4.

Contrarily, there can be a situation where all the unstable constituent systems combine to form an overall stable system by using appropriate switching signal. So, for the stability properties of the switched system, it is not sufficient to just consider the stability properties of subsystems only but we must also take into account the switching strategy as well.

The following two main issues regarding the stability of switched systems are pointed out in [43]:

- Find out the conditions to guarantee the stability of the switched systems under arbitrary switching.
- If the switched system is not stable for arbitrary switching then identify those signals for which it is stable.

The solution to the first issue has been found in terms of finding a Common Lyapunov Function (CLF). If we have a positive definite continuously differentiable function $V:\mathbb{R}^n \to \mathbb{R}$ then it is said to be a CLF if there exists a positive definite function $W:\mathbb{R}^n \to \mathbb{R}$ such that we have the following:

$$\frac{\partial V}{\partial x} f_i(x) \le -W(x) \quad \forall x,\ \forall i \in M \tag{2.7}$$

Based on the above we have the following theorem.

Theorem 2.1: If all systems in the family (2.3) share a radially unbounded CLF then the switched system (2.4) is Global Uniform Asymptotic Stable (GUAS). [43]

In many situations, a system is not stable for arbitrary switching, and it is only stable for few switching signals. There are other situations, when the switching strategy is already defined, thus the arbitrary switching is not available apart from a class of switching signals. In such situations where CLF does not exist we can analyze the stability of switched systems using Multiple Lyapunov Functions (MLF) [43], [44], [45].

Theorem 2.2: Let (2.3) be a family of globally asymptotically stable systems and let $V_i, i \in M$ be a family of corresponding radially unbounded Lyapunov functions. Suppose that there exists a family of positive definite continuous functions $W_i, i \in M$ with the property that for every pair of switching times

$\left(t_j, t_k\right)$, $j < k$ such that $\sigma(t_j) = \sigma(t_k) = i \in M$ and $\sigma(t_l) \neq i$ for $t_j < t_l < t_k$, we have

$$V_i(x(t_k)) - V_i(x(t_j)) \leq W_i(x(t_j)) \tag{2.8}$$

Then the switched system (2.4) is globally asymptotically stable. [43]

Proof: Let $M = \{1, 2, ..., m\}$ with m number of elements. Consider a ball of an arbitrary radius $\varepsilon > 0$ around the origin. Let us consider a set R_m contained in this ball and is of the form $\{x : V_m(x) \leq c_m\}, c_m > 0$. For $V_q(x(t_{j_1})), V_q(x(t_{j_2})), ...$, let R_j be a set of the form $\{x : V_j(x) \leq c_j\}, c_j > 0$ contained in the set R_{j+1}. Let us consider a ball of radius δ that lies in the intersection of all nested sequences of sets constructed for all possible permutations of $\{1, 2, ...m\}$. Let $|x(0)| \leq \delta$. If the first l values of σ are distinct with $l \leq m$ then by construction we have $|x(t_l)| \leq \varepsilon$. The values of σ will start repeating then and the condition (2.8) guarantees that the state will always belong to the one of the above sets (see Figure-2.5 for $m = 2$)

For the asymptotic stability, the finiteness of M implies that we have an index $q \in M$ with an infinite sequence if switching times $t_{j_1}, t_{j_2}, ...$, such that $\sigma_{t_j} = q$. The sequence $V_q(x(t_{j_1})), V_q(x(t_{j_2})), ...$ is decreasing and positive and thus has a limit $c \geq 0$. We have

$$\begin{aligned} 0 = c - c &= \lim_{k\to\infty} V_q(x(t_{j_{k+1}})) - \lim_{k\to\infty} V_q(x(t_{j_k})) \\ &= \lim_{k\to\infty} [V_q(x(t_{j_{k+1}})) - V_q(x(t_{j_k}))] \\ &\leq \lim_{k\to\infty} [W_q(x(t_{j_k}))] \leq 0 \end{aligned}$$

thus $W_q(x(t_{j_k})) \to 0 \,\text{as}\, x \to \infty$. Also W_q is positive definite. Therefore $x(t_{j_k})$ must converge to zero as $k \to \infty$. It then follows from the Lyapunov stability property that $x \to 0 \,\text{as}\, t \to \infty$ [43]. ■

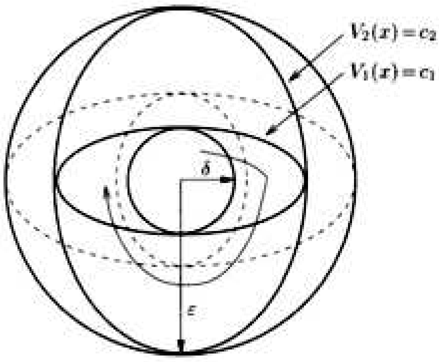

Figure-2.5 Lyapunov stability in theorem 2.2 [43]

In MLF, multiple Lyapunov functions corresponding to a certain subsystem are concatenated to produce an overall Lyapunov function of the system that might not be monotonically decreasing along the system trajectories. The switching signal can be restricted such that every time on switching from (i.e. exiting) a certain subsystem, its corresponding Lyapunov function is less than its value at previous existing time. Similarly the energy decreasing trend is captured by monitoring the Lyapunov functions values at entering instants [47], [48].

Note that each V_i decreases when the *ith* subsystem is active but it may increase when the *ith* system is inactive. This is shown in Figure-2.6 which is showing $V_i, i = 1, 2$ in which solid lines indicate the Lyanupov function for that mode when it is active and dotted lines indicate its value when the mode is inactive.

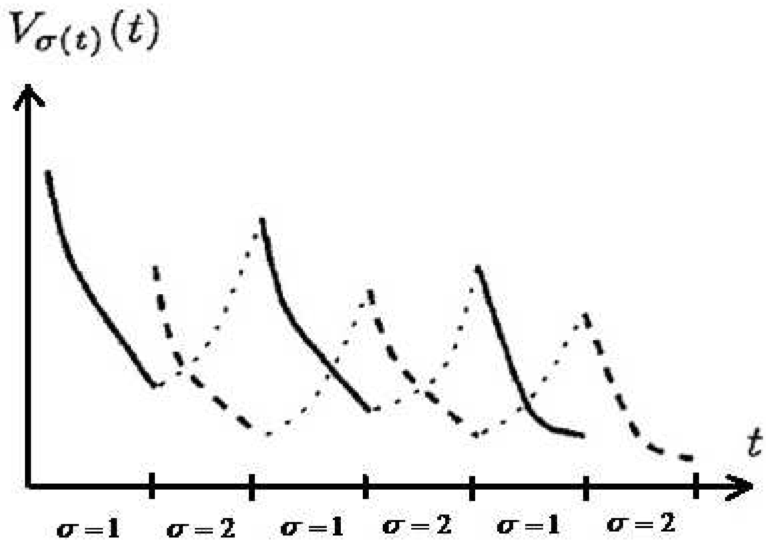

Figure-2.6 Multiple Lyapunov functions [43]

As discussed in the start of this Chapter that sliding mode technique is adopted in this dissertation for the state estimation of hybrid systems so second part of this chapter, starting from the next Section, is dedicated to introduce the relevant terminology in this regard.

2.4 Sliding mode control

Sliding Mode Control (SMC) is a form of Variable Structure Control (VSC) which was firstly explored in 1950 by Emelyanov and his co-researchers in Russia [49], [50]. In VSC, the controller is switched among various structures on the basis of certain rules to get the desired results. SMC is a variant of VSC and is basically a nonlinear design technique. Owing to its simple and robust design properties, this technique is equally applicable for linear as well as nonlinear systems with ease. SMC design consists of two phases; *reaching* and *sliding* [25]. In the first phase, a sliding surface $s(x)=0$ is designed and trajectories are forced towards this surface using the designed control law. Generally, sliding surface is constructed as a hypersurface or interaction of hypersurfaces in state space and is known as *switching surface*. In the second phase, the trajectories are kept on the sliding surface by the control law and steered towards the equilibrium point. The system in this state is said to be in *sliding mode*. Once the system is in the sliding mode it becomes invariant to parametric variations and model uncertainties/disturbances. The motion of the system in sliding mode is governed by reduced order dynamics. For a system with state vector of dimension n and input vector of dimension m, the dimension of state vector in sliding mode is $n-m$. This is described in the following example.

Consider a linear system of the form:

$$\begin{aligned} \dot{x}_1 &= x_2 \\ \dot{x}_2 &= a_3 x_1 + a_4 x_2 + bu \end{aligned} \tag{2.9}$$

where

$x \in \mathbb{R}^2$
a_3 and a_4 are system parameters
u is control input

Let us take a line of the form $cx_1 + x_2 = 0, c > 0$ passing through the origin. This line is called *sliding surface* or *hyperplane*.

Let

$$s = cx_1 + x_2 \tag{2.10}$$

The task of SMC is to enforce the system trajectories to be on this sliding surface i.e. to make

$$s = 0 \tag{2.11}$$

The reachiblity condition for ensuring convergence of system trajectories to the sliding surface is given below: (see Figure-2.7)

$$
\begin{aligned}
&\text{for } s > 0 \\
&\quad \dot{s} < 0 \\
&\quad \text{and} \\
&\text{for } s < 0 \\
&\quad \dot{s} > 0 \\
&\Rightarrow s\dot{s} < 0
\end{aligned}
\tag{2.12}
$$

From (2.10) and (2.11), we can find system dynamics on sliding surface as

$$
\begin{aligned}
&cx_1 + x_2 = 0 \\
&\Rightarrow x_2 = -cx_1 \\
&\Rightarrow \dot{x}_1 = -cx_1
\end{aligned}
\tag{2.13}
$$

We can see from (2.13) that during sliding mode, system dynamics are governed by a reduced order system. These dynamics are free of system's actual parameters. This property is called parameter invariance.

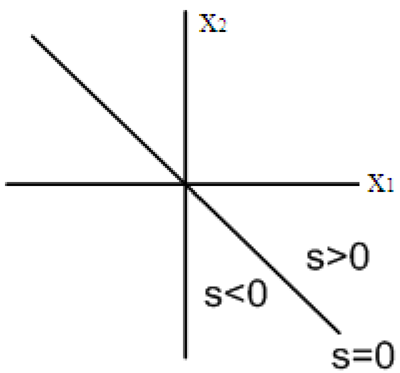

Figure-2.7 Sliding surface and reachibility condition

Along with its robustness and order reduction properties, the sliding mode technique also exhibits the finite time convergence property. With all these attractive features, sliding mode technique has some disadvantages as well, one of which is the chattering phenomenon. Chattering is the high frequency motion caused by imperfections of the switching devices, system inertia, delays and other factors. In the hybrid system literature the same phenomenon of infinite discrete transitions in finite time is studied under the heading of Zeno behaviors. Chattering can be harmful for the system and can damage the actuators etc. For this reason a lot of research work is conducted to solve this issue and several approaches can be found in the literature in this regard [51], [52], [53], [54], [55], [56].

2.5 Sliding mode observer

Many applications in control systems assume *a prior* availability of the state vector. This assumption is not valid in every situation, and sometimes, an estimate of system states is required. For this purpose, a dynamic system, known as observer, is used. The observer was first proposed and developed by Luenberger [57]. Sliding Mode Observer (SMO) uses concepts of the sliding mode technique to estimate system states and parameters in a robust and accurate way. SMC produces a control signal while SMO is used to produce an error residue. In the estimation process, the SMO tracks the actual measurement and generates an error signal by finding the difference between estimated and actual value [58]. Model uncertainty is accommodated by the SMO injection term that is designed to ensure the convergence of estimated states to the actual states of the plant. In contrast to the traditional Luenberger observer, SMO provides robust estimation of system states even in an uncertain environment. Moreover, traditional estimation approaches are mostly for linear systems and thus are accurate only in a specific operating region. SMO is a nonlinear technique that is equally applicable to linear as well as nonlinear systems. Therefore, we can directly apply it to nonlinear systems without linearizing the system around an operating point and thus can get accurate results for a broad region of operation. Furthermore, finite time convergence (being a special feature of sliding mode technique) of SMO is guaranteed. Below we describe SMO design procedure for a linear system to explain the above terminologies.

Consider a linear system represented as:

$$\begin{aligned} \dot{x}(t) &= Ax(t) + Bu(t) \\ y(t) &= Cx(t) \end{aligned} \tag{2.14}$$

where

$x \in \mathbb{R}^{n}$

$A \in \mathbb{R}^{n\times n}$ and is assumed to be a stable matrix

$B \in \mathbb{R}^{n\times m}$

$C \in \mathbb{R}^{p\times n}$

$y \in \mathbb{R}^{p}$

The SMO for this system can be designed as follows:

$$\dot{\hat{x}}(t) = A\hat{x}(t) + Bu(t) + K\mathrm{sign}(e(t)) \tag{2.15}$$

where

$\hat{x}(t)$ represents state estimate

K is observer gain

$e(t)$ represents error given as $e(t) = x(t) - \hat{x}(t)$

$\mathrm{sign}(.)$ is defined as

$$\mathrm{sign}(e) = \begin{cases} -1 \text{ if } e < 0 \\ \ \ 0 \text{ if } e = 0 \\ \ \ 1 \text{ if } e > 0 \end{cases}$$

The error dynamics can be obtained by using (2.14) and (2.15) as:

$$\dot{e}(t) = Ae(t) - K\mathrm{sign}(e(t)) \tag{2.16}$$

For sufficiently large value of *K*, the estimated states converge to the actual values and we get

$e(t) \to 0$

To illustrate the above procedure, a simulation example is presented below.

Consider a linear system representing simple harmonic oscillator given as: [59]

$$
\begin{aligned}
\dot{x}(t) &= Ax(t) + Bu(t) \\
y(t) &= Cx(t)
\end{aligned}
\tag{2.17}
$$

where

$$
A = \begin{bmatrix} 0 & 1 \\ -2 & 0 \end{bmatrix}, B = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, C = \begin{bmatrix} 1 & 1 \end{bmatrix}
$$

For simplicity, take $u(t) = 0$

SMO designed for (2.17) is given as

$$
\dot{\hat{x}}(t) = A\hat{x}(t) + Bu(t) + K\text{sign}(e(t)) \tag{2.18}
$$

where terms used are already defined. For this example *K*=5.

Error dynamics is obtained from (2.17) and (2.18) as:

$$
\begin{aligned}
\dot{e}_1 &= e_2 - K\text{sign}(e_1) \\
\dot{e}_2 &= -2e_1 - K\text{sign}(e_2)
\end{aligned}
\tag{2.19}
$$

The simulation results are presented in the following figures.

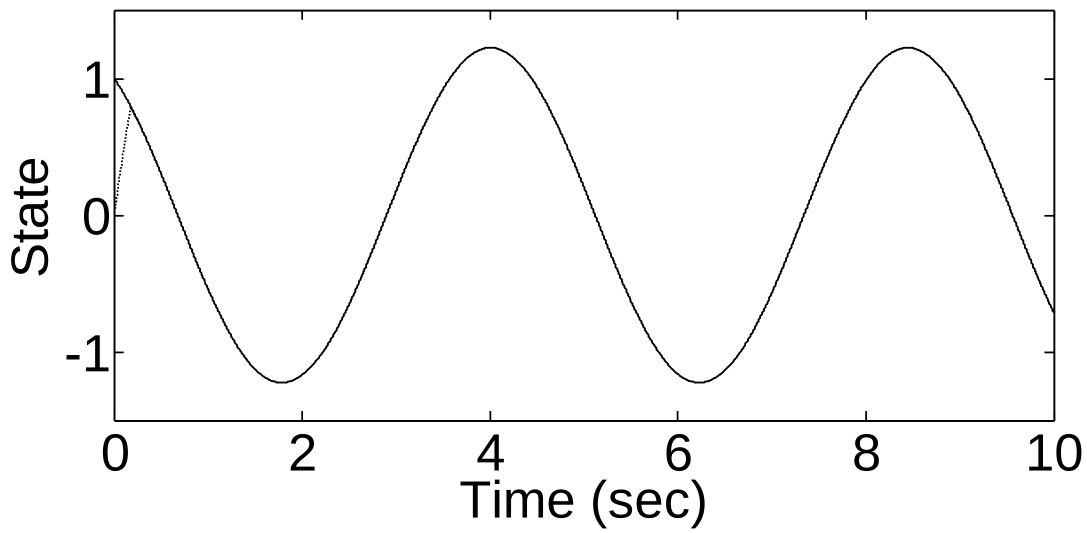

Figure-2.8 x_1 and its estimate

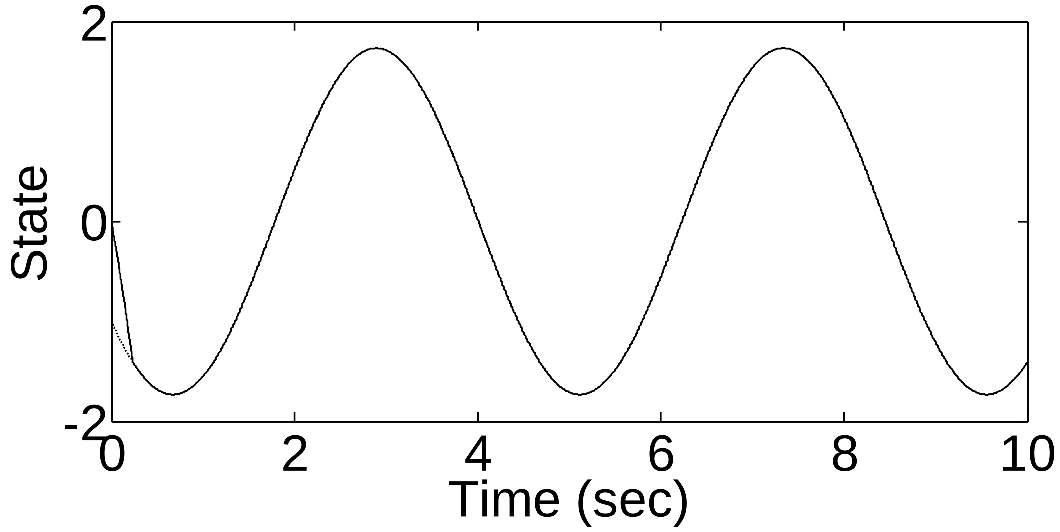

Figure-2.9 x_2 and its estimate

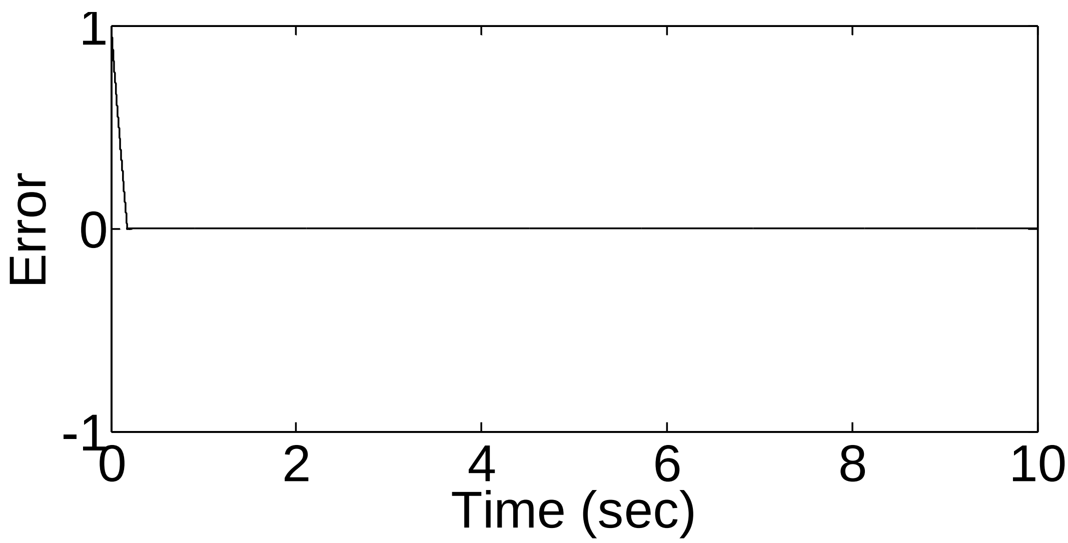

Figure-2.10 Observer tracking error e_1

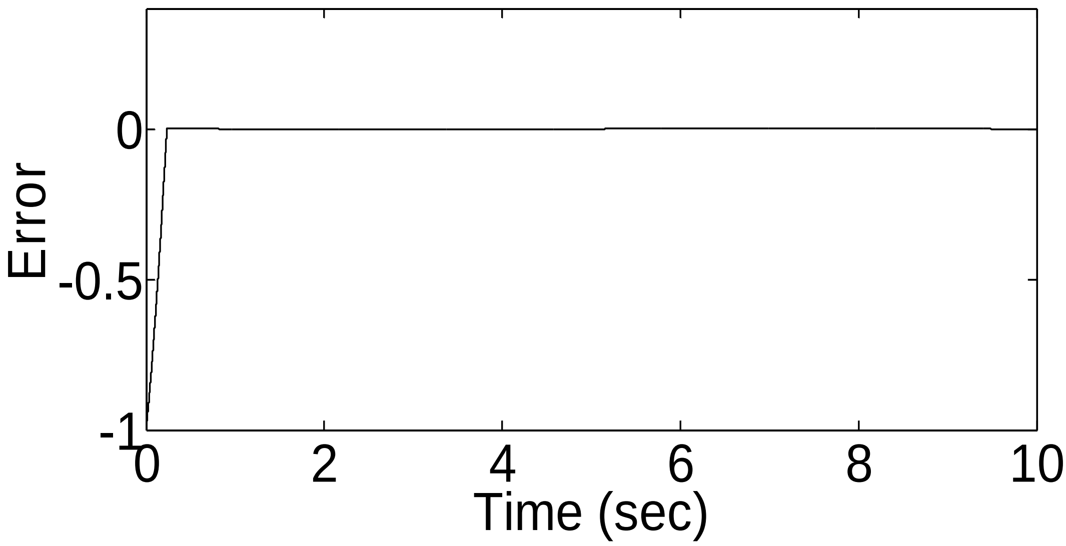

Figure-2.11 Observer tracking error e_2

Figure-2.8 shows the actual x_1 and its estimate. Similarly Figure-2.9 gives the estimation of x_2 along with x_2. The solid lines in these figures represent the actual states and dotted lines indicate their estimates. The initial states for model are taken as $x_1 = 1$ and $x_2 = -1$. The observer tracking error is shown in Figure-2.10 and Figure-2.11.

2.6 Summary

This chapter provided important background required for the upcoming chapters. The chapter mainly consists of two parts: first part is about the hybrid systems and the second part discusses the sliding mode technique.

The first part of this chapter gives an introduction to the hybrid systems and the related terminology. An important class of the hybrid systems, known as switched systems, is discussed. Moreover, this part also contains discussion about different types of the switching. Another important factor discussed is the stability of the hybrid system that not only depends on the individual subsystems but also on the switching signal.

The second part of this chapter gives the introduction to the sliding mode technique and the related terminology. The main topics covered are the design process of SMC and SMO along with their benefits and drawbacks. A simulation example is also presented to illustrate the SMO design process.

In the next chapter, the FDI terminology and related work for the hybrid systems is described.

CHAPTER 3

FDI OF HYBRID SYSTEMS

This chapter introduces terminologies relevant to the FDI and previously devised approaches for this purpose. This chapter starts with the description of the FDI standard terminology given in Section 3.1, adopted from the International Federation of Automatic Control (IFAC) workshop on SAFEPROCESS in 1996. Section 3.2 gives the fault classification. In Section 3.3, we discuss different fault diagnosis schemes for the linear and the nonlinear systems and Section 3.4 discusses different fault diagnosis schemes for hybrid systems with their pros and cons. Mode identification in hybrid systems is an important topic that is covered in Section 3.5. Finally Section 3.6 concludes this chapter.

3.1 FDI terminology

The work in the FDI had been initialized in 1970s, however, the FDI terminology was not consistent during those times. With the advancement of technology, the systems become more efficient, yet more complex. Hence, the significance of the FDI has been enhanced due to the requirement of the reliable and safe operation of these systems and a standard terminology for FDI has been formulated. For this purpose a steering committee called SAFEPROCESS was formed within IFAC in 1991. In the following we start with the basic FDI terminologies given in [59].

3.1.1 Fault

Fault is defined as an un-permitted deviation of at least one characteristic property of a variable from an acceptable behavior. It should be noted that the fault occurrence does not necessarily mean that the system has stopped working. The system can be still working but with the degraded performance.

3.1.2 Failure

Another related concept is the failure which is defined as the permanent inability of a system to perform a desired task under given operating conditions. For instance, a small leakage in the cooling system of an automobile can be termed as a fault, whereas, if the coolant amount in the system drops beyond a certain threshold value, it can result in the system failure.

3.1.3 FDI

Fault Detection and Isolation (FDI) is related to the monitoring of the systems in order to identify the faults and pinpoint their locations. A more advanced term is known as Fault Detection, Isolation and Identification (FDII). Fault detection means to detect the occurrence of a fault in the system. Fault isolation is the process of identifying the faulty component. Fault identification provides an indication of the severity of the fault.

3.2 Fault classification

Faults are normally classified on the basis of time, location, and modeling. In the following we briefly describe these classifications.

3.2.1 Fault classification based on time

The fault can be classified in the following three categories based on time [60]

- Abrupt Faults
- Intermittent Faults
- Incipient Faults

3.2.1.1 Abrupt faults

In this type of the fault, the time between the fault occurrence and its appearance is very small. These faults are relatively easier to detect because of abrupt change in the system parameters coupled with the fault. Few examples of the abrupt fault include sudden fall of the actuator gain to some extent of the desired value, actuator jamming etc.

3.2.1.2 Intermittent faults

This type of fault appears and disappears at the discrete intervals. Few examples of the intermittent faults are loose electrical connection, misfiring in engine cylinder at different intervals etc.

3.2.1.3 Incipient faults

These faults are usually caused due to wear and tear of the components. Faults of this type grow slowly and regularly with time. Their impact on a system becomes noteworthy only when their magnitude increases beyond a certain level. For this reason, these faults are difficult to detect at their initial level. A slow drift in sensor is an example of an incipient fault.

Figure-3.1 shows the time behavior of these three fault types.

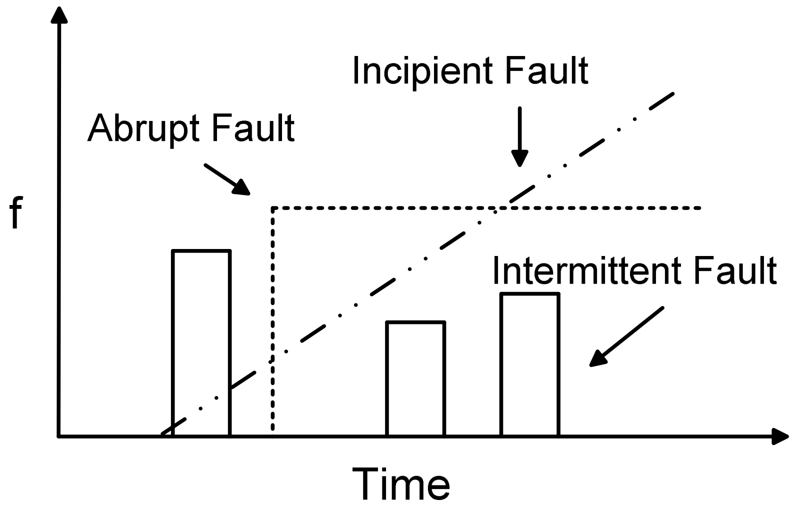

Figure-3.1 Time-based classification of faults.

3.2.2 Fault classification based on location

Based on the location the faults are categorized in the following three types.

- Actuator faults
- Component faults
- Sensor faults

3.2.2.1 Actuator faults

Actuators are responsible for converting the control commands into the actuation signals. Actuator faults can result in the failure of the commands execution by the controller. The most common actuator faults include lock-in-place, hardening and loss of effectiveness of the actuator.

3.2.2.2 Component faults

Faulty components result in the performance degradation or failure of the system. This can be viewed by monitoring the system behavior using system states or parameters because these faults appear as the change in system parameters. In general, the component faults occur due to the wear and tear and aging of the system components. Common examples of the component faults include breakage, cracks, leakage, filter clogging etc.

3.2.2.3 Sensor faults

The system information is normally collected by the controller through sensors. Therefore, a fault in the sensors can directly impact the controller performance. The common faults that occur in the sensor are bias, drift, freezing and loss of accuracy. Bias indicates an offset in the sensor reading from that of the actual value. Drift represents the change in sensor output from that of the actual value with time. In case of freezing fault, the sensor shows a constant value throughout the process. In case of loss of accuracy, the sensor gives the output value that is quite different from the actual value.

3.2.3 Fault classification based on modeling

Faults can also be classified in the following two classes based on the way they are modeled [60]

- Additive faults
- Multiplicative faults

3.2.3.1 Additive faults

This type of the fault affects the system output by an offset and can be expressed in terms of addition in model. These faults are normally due to the disturbances and noise. The actuator and the sensor faults can be conveniently represented in terms of additive faults.

3.2.3.2 Multiplicative faults

Multiplicative faults occur due to the change in the system parameters and they are expressed in terms of multiplication with system parameters or states. Component faults can be easily modeled as multiplicative faults.

Figure-3.2 gives the description of these faults, where Y(t) represents system output, U(t) represents the input of the system, f represents the system fault and G represents the system model.

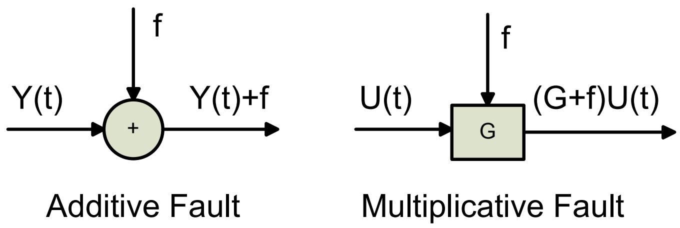

Figure-3.2 Modeling based classification of fault

3.3 Fault diagnosis schemes

Fault diagnosis schemes can be broadly categorized in two types [61]:

1) Model-free approaches
2) Model-based approaches

3.3.1 Model-free approaches

In many cases—for instance, in chemical plants or process industries—the system model is either unavailable or too complex to be suitable for FDI purpose. In these situations, model-free approaches are suitable choices that do not use the system model in the FDI process. Model-free approaches can be broadly classified as:

- Signal-based approach
- Plausibility check
- Hardware redundancy

The description of each one of these is given as follows:

3.3.1.1 Signal-based approach

In signal-based approach, the process signal properties are used for the FDI purpose. These signal properties include magnitude, trend, limit check, statistical properties etc.

Figure-3.3 gives a description of this scheme. A fault in the actuator, sensor or system varies the signal properties that are analyzed using signal processing techniques for the FDI. In [62], the authors adopted this approach for the engine fault diagnosis. However, signal-based fault diagnosis is mostly used in steady state conditions and its efficiency is limited in the processes with wide operating range [63].

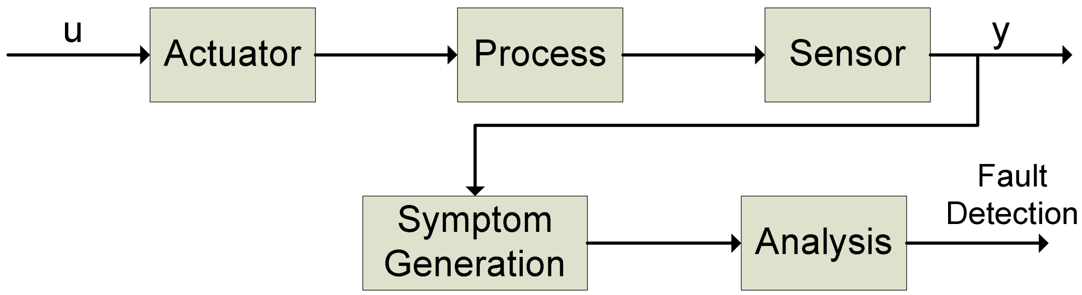

Figure-3.3 Signal-based fault detection

3.3.1.2 Plausibility check

Plausibility check is performed by testing the plausibility (i.e. apparently valid) of the sensor measurements. Such checks are normally conducted by validating the measurements against their expected behavior like the measurement sign etc. However, plausibility check is not efficient in the complex systems and is suitable only for simple applications. Figure-3.4 gives a schematic description of the plausibility check approach.

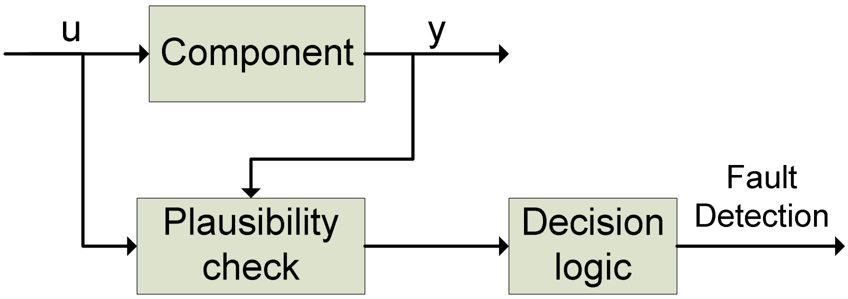

Figure-3.4 Plausibility check approach

3.3.1.3 Hardware redundancy

In hardware redundancy, additional redundant components are installed for the FDI purpose. Process output is compared with the output of redundant component for the fault detection purpose.

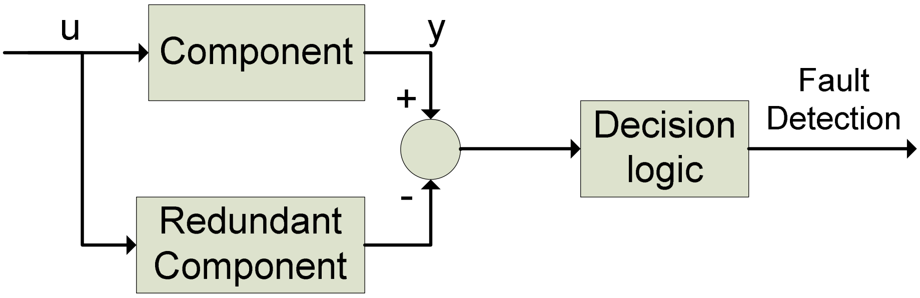

Figure-3.5 Hardware redundancy approach

The main advantage of this approach is reliability and direct isolation of fault. However, due to the additional hardware the major disadvantages associated with this approach are extra hardware along with increase in the cost, weight and size. Figure 3.5 gives a schematic depiction of this approach.

3.3.2 Model-based approaches

Model-based FDI approach replaces the hardware redundancy by using the process model in parallel to the system under observation. The model used for the analytic redundancy can vary but the structure of the model-based FDI scheme mainly consists of the following parts as shown in Figure-3.6:

- Residual generation
- Residual evaluation
- Threshold definition

One of the most popular model-based FDI methods, for continuous dynamical systems, is observer-based FDI approach. Observer-based FDI generates a residual signal by comparing the estimated values of measurement with the actual measurements. Residual gives indication of any mismatch between observed behaviors of system from that of desired. Under ideal conditions, this residual value is zero in case of fault-free system. However, due to the presence of disturbances and model uncertainties this residual is not exactly zero even in the fault-free case. Therefore a threshold is selected such that the residual crosses the threshold in case of occurrence of a fault [63]. The selection of this threshold is crucial in the FDI process as too low a threshold results in false alarm and too high a threshold results in missing some faults detection. To solve this problem, the concept of variable threshold was introduced in the literature [63], [64].

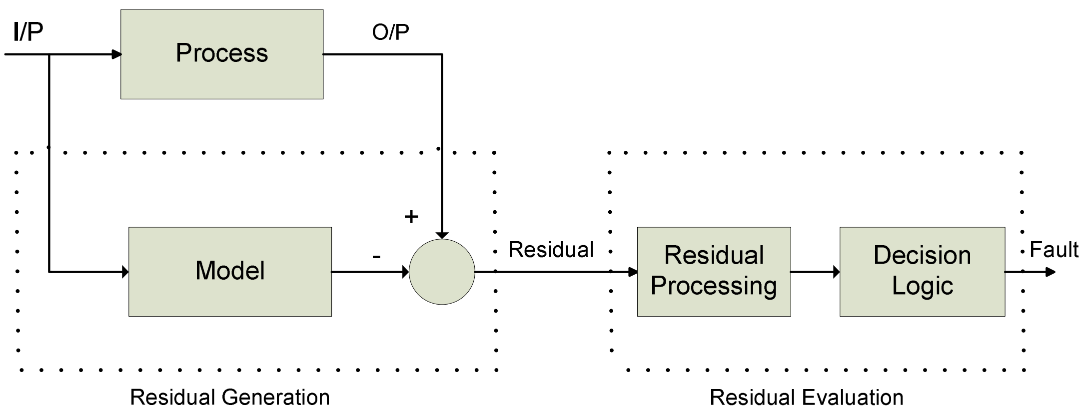

Figure-3.6 Model-based fault diagnosis

Based on the model used for the FDI purpose, we can further divide model-based FDI approaches as follows:

- Analytical models
- Knowledge-based models

3.3.2.1 Analytical models

Analytical models are usually represented by the differential equations. The three famous approaches under this category are:

- Parity space approach
- Observer-based approach
- Parameter estimation approach

Each one of these is discussed below:

3.3.2.1.1 *Parity space approach*

This approach is based on the consistency check of the parity equations. In this approach, the measurements obtained from the system are used to derive a set of properly modified equations (known as parity relations) that decouple the states from the residuals. The parity equations can be obtained either from the state space model [65] or from the transfer function of the system [66]. In the parity space approach, same input is applied to the system as well as parity space equation and residual is generated by finding the difference in the actual measurement and the model output. The authors of [67] used parity relations for the FDI of the SI engine. [68] used parity relation for the fault diagnosis of a class of nonlinear systems. Parity space approach, however, is sensitive to the noise effects.

3.3.2.1.2 *Observer-based approach*

This is one of the most widely used model-based fault diagnosis approach. In the observer-based FDI approach, an observer is used to generate the estimate of the actual measurement. This estimate is used along with the actual measurement from the system to generate the residual signal. One should note that there is a difference between observers used for control purposes and for the fault diagnosis purpose. The former are state observers used to estimate the unknown states while the later are the output observers used to estimate the measurements. The idea of using observers for the FDI started in early 70's and later research in this field focused on the robustness of the residual signal against disturbances and measurement noise [69], [70], [71], [72].

3.3.2.1.3 *Parameter estimation approach*

Estimation of critical parameters of the system can be a useful way of the fault detection [73]. The parameters of a system reflecting system health can be estimated and analyzed for the fault diagnosis purpose. These estimated parameters can be compared against their normal operating values for the detection of fault. The commonly used approaches under this category are

- Least square method
- Kalman filter
- Sliding mode technique

Each of these is described below.

The least square and its variants have been successfully used for the fault diagnosis purpose [74], [75]. In this method, model of the system is predicted using the input data by minimizing the squared sum of the residuals. The relevant parameters, critical to system health, are then analyzed for the fault detection. This method, however, provides offline estimates of the linear systems.

Kalman filter is most widely used for the state and parameter estimation of systems in stochastic settings. In case of parameter estimation using Kalman filter, the required parameters need to be represented as additional state variables i.e. the original state vector is augmented with these state variables and is known as augmented state vector. The Kalman filter approach is applicable to the linear systems and uses system linear model along with *a prior* information of the process noise distribution. For the nonlinear systems, we have to use a variant of Kalman filter known as Extended Kalman Filter (EKF). The estimation algorithm in Kalman filter uses system *a prior* information to generate initial estimates and then improve them recursively using its gain. The approach of Kalman filter for state and parameter estimation, however, requires *a prior* information about the process and needs to linearize the nonlinear system on the operating point.

Sliding mode technique is vastly used by control community for the state and parameter estimation due to its finite time convergence, simple design and robustness against uncertainties [14], [17], [19], [20], [21], [22], [23], [24]. SMO is used to estimate system states and parameters by tracking actual measurements. In contrast to the Kalman filter, it does not need to linearize the system on the operating point and is equally applicable to linear as well as nonlinear system. Moreover, it is simple in design and easy to implement online. However, First Order Sliding Mode Observer (FOSMO) suffers from chattering that can be taken care of by High Order Sliding Mode Observer (HOSMO).

3.3.2.2 Knowledge-based models

This approach is useful in situations in which the system model is too complex or hard to find. Knowledge-based models can be represented by fuzzy logic, neural networks etc. The residual is generated using the knowledge-based model along with a symptom table.

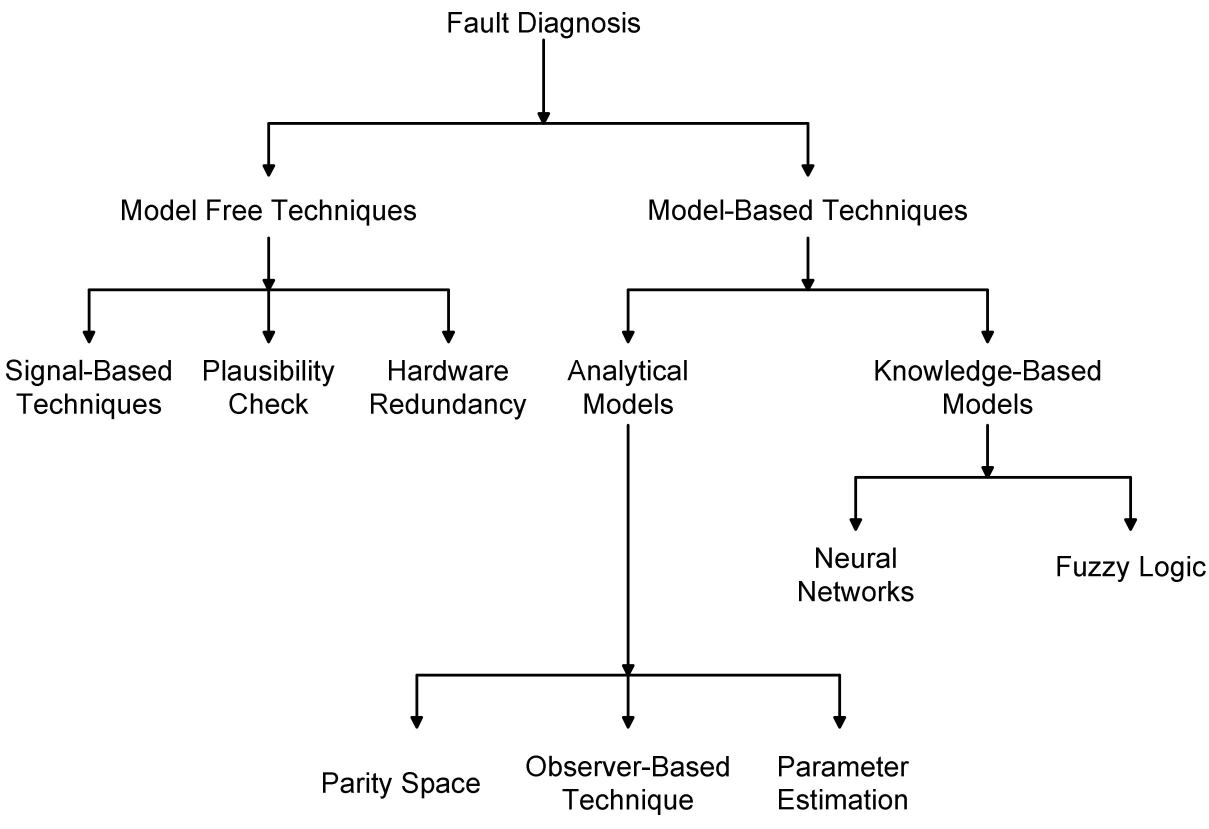

Figure-3.7 Fault diagnosis approaches

3.3.2.2.1 *Neural networks*

In this approach, the model used to provide analytic redundancy is composed of neurons, input and output layers. Neural networks require training data for each class. Once the training phase is completed, the model can be used for fault diagnosis. This approach, however, suffers from the lack of availability of large number of training samples required for efficient fault diagnosis.

3.3.2.2.2 *Fuzzy logic*

In this approach, the model used to provide analytic redundancy is formed from the fuzzy rules. These rules provide the symptoms for faulty and healthy operation as defined in fuzzy reference sets. Using this approach, fault detection is performed by comparing the rules of reference models with the rules of partial fuzzy model obtained from the actual fault-free measurements of plant. This approach, however, requires expert knowledge and offline training data before it can be applied for the fault detection.

Figure-3.7 gives a summary of different fault diagnosis schemes discussed so far. This Section provided a review of the fault diagnosis approaches generally used for the dynamical systems. In the next Section, we review fault diagnosis techniques used for the hybrid systems monitoring.

3.4 Fault diagnosis schemes for hybrid systems

As mentioned in Chapter 1, hybrid systems involve both the discrete and the continuous dynamics that have to be monitored for the reliable operation of the system. Due to the simultaneous presence of the both dynamics, chances of fault in these systems become higher and thus for the same reason they become more difficult to diagnose than the conventional systems. To ensure their safe and reliable operation an efficient FDI scheme is required. A general approach to study these systems was to approximate them either as purely continuous or discrete systems, suppressing the effect of one dynamics and concentrating on the other. This approach has few advantages e.g. a system model designed for specific application area needs not to cover all the details of the system thus liberating from the avoidable complexity.

Moreover, in using this approach, standards algorithms and well established techniques are readily available from the corresponding domain for use on the system under study. However, in more sophisticated applications like the nuclear power plants, space shuttles and aerial vehicles etc, ignoring/suppressing a dynamics can result in significant loss. Moreover, the use of the FDI scheme from the corresponding single domain can result in the overlooking of the important fatal faults. Purely discrete event approaches for the FDI of the hybrid systems might not be able to detect faults reflecting in the system continuous behavior. Similarly, purely continuous approaches might not always be suitable for the FDI of these systems as they can result in complicated nonlinear behavior and thus become difficult to implement in the real world.

Another important factor that should be taken care of in the FDI of the hybrid systems is the identification of the active mode among various modes of the hybrid system. This is so because in these systems, the threshold crossing by the generated residual in the model-based FDI may not necessarily be an indication of a fault but it can be due to the mismatched modes and thus can result in the false alarm. Also in the observer based FDI approaches, the active mode of the hybrid system is required for the estimation of the states used in the process of the residual generation. Besides these factors, the identification of the active mode can also be used for the FDI of the hybrid systems as the deviation of the mode occurrence sequence from that of expected sequence can be used for the fault detection in the hybrid systems. The mode identification, therefore, is a key step and natural way in the identification and monitoring of the hybrid systems.

Due to its inherently multidisciplinary nature, researchers from various back grounds became interested in these systems. Two communities actively working in these systems are the control system community and the computer science community. The emphasis of the computer science community is mainly on the discrete behavior of these systems and they give little attention to the continuous dynamics. The control system researchers, on the other hand, mainly focus on the continuous dynamics and approximate the hybrid systems as continuous systems with switching. These both approaches come up with some pros and cons e.g. the system model that is adopted in the model-based FDI approach is just an approximation of the actual system and have modeling uncertainties in it. A more accurate and detailed model of the system can take care of this issue but this will increase the complexity of the algorithm and the resulting solution might not be suitable for the online implementation. Similarly, the data based FDI methods lack the details of the physical link of the algorithm. A useful FDI approach can be to integrate the methods from these two communities to utilize the positive features of both and avoid the negative ones that should result in better and improved performance.

Several existing approaches that can be found in the literature for the FDI of the hybrid systems are [7], [76], [77], [78], [79], [80], [81], [82]. A petri-net approach is used in [7] to form a timed abstraction of the hybrid systems. For this purpose, a fault symptom table is produced, which is used to form a decision tree offline. This method, however, requires experience and the domain specific knowledge for constituting the fault symptom table. Moreover the use of the decision tree confines the approach to the assumption of only one fault at a time. In [76], the structured parity residuals have been used for the FDI of the hybrid systems. Two fault types have been considered in this case: the ones related to the current mode behavior, and the ones affecting the discrete evolution trajectory. However this approach cannot be easily extended for the nonlinear systems. In [77], a Hybrid Bond Graph (HBG) is used in the FDI of the hybrid systems that uses a hybrid observer consisting of the Kalman filter and a mode change detector. However, Kalman filter requires prior system and noise information. Moreover, it is computationally heavier than the SMO since the former requires several matrix calculations. Furthermore, the Kalman filter cannot be used for the nonlinear systems directly and we have to use the EKF for this purpose which involves further calculations like calculating Jacobian based linearization etc. In [78], the state estimation is used for the FDI of the hybrid systems. The authors of [78] proposed a mode observer and a continuous observer using bank of the Unknown Input Extended Kalman Filter (UIEKF). This suffers from the same issues of Kalman filter mentioned above. Moreover, the dedicated mode observer can be replaced by adopting the approach of [30] that provides simultaneous estimation of the discrete and the continuous states using the SMOs. The approach used in [80] requires an excitation signal for the fault diagnosis purpose. Another approach used for the fault diagnosis of the hybrid systems is the particle filter approach [81], [82]. The issue with this approach is that of the sample impoverishment (reduction of particle diversity, which in the extreme cases results in "collapsing" of all the particles into a signal particle [83]) that decreases the probability of the transition to the faulty state.

The major issues in the existing FDI approaches for hybrid systems are summarized below:

- A general approach to study these systems was to approximate them either as purely discrete or continuous system. This approach is useful in the sense, that depending upon the application, if some details can be ignored then we get a simplified version of the system for the control and analysis purposes. However, in more sophisticated applications, ignoring such details can result in significant loss. Moreover such simplified representations can also skip the details that can be useful for the FDI purpose.

- Some existing FDI techniques for hybrid systems consider only either the discrete fault or continuous fault and not both at the same time. Most of the techniques that consider both types of fault simultaneously are not able to distinguish the fault type since the residual used in the FDI process can be affected in the same way by both faults. Our proposed scheme differentiates between these residuals and is not only able to detect and isolate the fault simultaneously but also identifies the fault type using the same scheme.

- Conventional model-based FDI approaches cannot be directly applied to the hybrid systems as the inconsistency indicated by the residual in the FDI process can also be due to the mode mismatch. So we have to identify the operating mode before the application of the estimation technique in the FDI process. Moreover these identified modes can be used to develop novel FDI approaches to capture both types of faults simultaneously.

- The class of approaches that use observer in the FDI process suffers from the following issues.
    - Use of bank of Luenberger observer or Kalman filter in the FDI process as compared to our proposed approach the uses bank of SMO for the FDI purpose. Luenberger observer can be directly applied to the linear systems only and is not a robust approach. In hybrid systems

where switching is involved we need a robust approach for the accurate of the state estimation. Similarly Kalman filter is directly applicable to the linear systems only and is computationally heavier than the SMO. Moreover it requires prior information about the system noise. Furthermore if we extend it for the nonlinear systems then it involves more computations.

  - The existing approaches for the FDI of hybrid systems use a dedicated mode observer for the identification of the active mode and a dedicated scheme for the estimation of continuous states, while we are adopting an approach involving SMOs that simultaneously estimates both states through single scheme.

- Class of the probabilistic FDI approaches for hybrid systems is unable to handle the unknown faults (un-modeled behaviors of system) as they use the observations history to develop a probability distribution over system states to find the information of the present possible states [84]. In the FDI approach we are using, new modes are added to handle these unknown faults.

3.5 Mode identification in hybrid systems

Mode identification refers to the estimation of active mode from various modes of hybrid systems. It is a key step in the identification and monitoring of the hybrid systems. The problem of mode identification in the hybrid systems is actively explored by the researchers in the last decade or so [6], [7], [8], [30], [31]. The authors in [6] used the consistency of Analytical Redundancy Relations (ARR) for the mode identification purpose. They adopted HBG model for generating the ARR. HBG models the discrete mode changes by using switching junctions. In [7], a discrete model based approach is adopted for mode identification and the authors used a timed Petri net to focus only the discrete dynamics. This model is used to generate event predictions by focusing the signal processing algorithms. In [8] 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. [30] used the injection signal of SMO for the estimation of active mode of the SLS. The advantage of using SMO is the simultaneous estimation of both the active mode and the continuous state of the SLS. Another approach using SMO for mode estimation is presented in [31]. This approach features a finite time converging estimate and recovers both the active mode and continuous state. Sliding mode technique has been widely used by the control industry in different applications. Owing to its simple and robust design properties, this technique is equally applicable for linear as well as nonlinear systems with ease. This trend is now shifting towards hybrid systems as well to get the benefits of this technique for these systems.

In the present work, we are using mode identification for the FDI of hybrid systems by defining healthy and faulty modes. In the hybrid systems represented through hybrid automaton model, the interaction between discrete dynamics and continuous dynamics is defined through invariants and transition relations. Each mode has an associated invariant that contains the conditions the continuous state has to fulfill at this mode. Similarly each transition between modes has an associated transition relation that describes the conditions on the continuous state under which that transition can occur [41]. On the event of fault occurrence, the continuous state of the system does not satisfy the invariant related to that particular mode and transition occurs from healthy mode to, what we call as faulty mode, under a transition relation. So we can estimate and analyze the continuous states of the system to identify the healthy or faulty mode. However, in case of hybrid systems, two types of faults can be considered: the ones related to the current mode behavior and the others affecting the discrete evolution trajectory. To detect this second type of fault, we have to identify and monitor modes sequence as well. Instead of using two different schemes for detecting these both types of fault, we devise a single scheme for this purpose. This is the topic discussed in the next chapters.

3.6 Summary

In this chapter, we discussed various terminologies used in the FDI process. We have also discussed different types of fault depending upon location, time and modeling. Then we discussed various fault diagnosis techniques used for the linear and nonlinear systems and later on the state of the art techniques used by the researchers for the FDI of hybrid systems are discussed. Process of mode identification and its use in fault diagnosis is also described in this chapter.

The terminology and concepts presented in this chapter will be useful for the upcoming chapters that present the proposed mode identification scheme for the FDI of the SLS.

CHAPTER 4

MODE IDENTIFICATION SCHEME FOR THE FDI OF SLS – PART I

In this chapter, we present a mode identification scheme for the FDI of an important class of the hybrid systems known as Switched Linear Systems. The presented scheme estimates the system states using SMO and analyzes these states in the mode identification for the FDI purpose. These modes appear at the input of a Deterministic Finite Automata (DFA) as symbols of a language acceptable to it. The DFA process this stream of symbols in search of a fault. New faults can be detected and isolated by introducing new strings. The proposed algorithm is illustrated through a simulation example by applying it to a switched linear model.

This chapter starts with an introduction to the proposed scheme. Section 4.2 describes the proposed FDI scheme. Section 4.3 demonstrates the application of the proposed scheme through a simulation example. Section 4.4 concludes the whole work.

4.1 Introduction

As described in Chapter 1, any deviation in the expected mode sequence of a hybrid system can be used for the fault indication. The standard FDI literature provides several approaches for the fault detection and isolation of the dynamical systems, one of which is based on the state estimation. For the FDI of the hybrid systems, testing of the mode sequence along with the analysis of the continuous states can be used to evolve simpler methods. This corresponds to the state estimation based fault detection of dynamical systems with some additional work load to develop a generalized fault detection scheme for the hybrid systems. The existing FDI techniques for the hybrid systems utilize dedicated mode observer for the active mode identification and the continuous observer for continuous state estimation that are analyzed for the FDI purpose (see Section 3.4). Generally, bank of Kalman filters is used for the estimation of the continuous states of the hybrid systems. However, Kalman filter is directly applicable only on the linear systems and also requires *a prior* information about process noise. For the nonlinear systems, one has to use EKF that requires further calculations in linearizing the system on the operating point. On the other hand, SMO is a nonlinear robust estimation technique that is directly applicable to the nonlinear systems without the need of linearization on the operating points. Sliding mode technique alters the dynamics of the system by forcing it to a manifold and can be used for the robust estimation of states even in the uncertain conditions. Moreover, Kalman filter is computationally heavier than SMO as the former requires calculations of several matrices during its operation. Due to these features, we adopted SMO for the state estimation that will be analyzed for the fault diagnosis purposes. Another advantage of the SMO is the vanishing of the requirement of the dedicated mode observer by the simultaneous estimation of discrete and continuous states as presented in [30].

As mentioned in the previous chapter, two types of faults can be considered in the hybrid systems. These faults can be diagnosed by monitoring the continuous and discrete states separately. However, if these states can be translated in terms of each other, then a single technique can be developed for the diagnosis of these both types of fault in the hybrid systems. If we assume the mode (whether healthy or faulty) of a hybrid system as a symbol of a language, then any possible combination of modes can be considered as the string of that language. Therefore, a set **F** of system faults can be defined that contains all those combinations which correspond to the various faults in the system. The detection and identification of new faults can be easily accommodated by introducing new strings in the fault set **F**. The set **F** can be formed by identifying signal features [85], defining functions to fulfill specific needs [86] or integrating qualitative knowledge of systems in the form of rules or constraints [87]. The process of the FDI is thus reduced to the detection of strings and to check whether they belong to the set **F**. The fault detection process can therefore be divided into three major steps:

- Symbol generation
- Generation of a valid string
- Analysis of string to identify that it belongs to set **F**

The proposed FDI technique exploits the fact that deviation of the mode sequence from that of expected can be used for the fault diagnosis. For the analysis of mode sequence, a Deterministic Finite Automaton (DFA) design is proposed to be used in the FDI of the SLS. The proposed DFA takes the identified modes, represented as the symbol of a language, as the input. The use of the proposed DFA in the FDI of hybrid systems enables us to diagnose these both types of fault simultaneously and using the same DFA structure. Our proposed algorithm starts with the state estimation of the active mode using the SMO. In the later part of the algorithm these estimated states are translated into string of symbols and finally the DFA analyze this string to identify the fault.

4.2 The proposed scheme

Consider a switched linear system with m subsystems represented as:

$$\begin{aligned} \dot{x}(t) &= A_{j(t)}x(t) \\ y(t) &= Cx(t) \end{aligned} \tag{4.1}$$

where $X \in R^n$ represents the state vector, $y(t) \in R^p$ represents the output vector and $j(t) \in M = \{1, 2, ..., m\}$ determines the active system dynamics among the m possible subsystems.

It can be observed that for a fault event in the active subsystem of the hybrid system, it switches from “healthy mode” to a new mode, named as “faulty mode”. Thus we have

$$\begin{aligned} \dot{x}_f(t) &= \bar{A}_{p(t)}x_f(t) \\ y_f(t) &= Cx_f(t) \end{aligned} \tag{4.2}$$

where $p(t) \in \bar{M} = \{m+1, m+2, ..., 2m\}$ determines the faulty system dynamics among the m possible faulty subsystems i.e. for each healthy subsystem, a corresponding faulty subsystem exists that will be active on the corresponding fault event. Now the complete mode set is given as:

$$M_c = M \cup \bar{M} \tag{4.3}$$

We assume that each subsystem has only a single fault related to it. Moreover, only one subsystem can be faulty at a time and no fault is assumed to occur at switching times.

Definition 4.1

A non-empty set S_a is said to be *admissible set* if it contains only those mode switching sequences that result in the non-faulty behavior of (4.1).

It is clear from the above definition that

$$p(t) \notin s_a, \ \forall p(t) \in \bar{M} \ \ \forall s_a \in S_a . \tag{4.4}$$

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

For the symbol generation, we analyze the states of the system. These states might not always be available and so we have to estimate them. Therefore we first describe the state estimation process as under.

States of the SLS given in (4.1) are estimated by adopting the approach of [30]. Following assumptions are made for this.

Assumption 1: The minimum dwell time between any two mode switching is known i.e. $t_k - t_{k-1} \geq \Delta > 0$ where Δ is known constant greater than zero and $t_k (k = 1, 2, ...)$ are the switching time instants with $t_0 = 0$.

Assumption 2: The matrix pairs (A_i, C), are observable for all $i = 1, 2, ..., m$.

Consider the state transformation given in [58] such that output appears as part of the state vector i.e.

$$T_c x = \begin{bmatrix} \psi \\ y \end{bmatrix} \begin{matrix} \updownarrow n-p \\ \updownarrow p \end{matrix} \tag{4.5}$$

with

$$T_c = \begin{bmatrix} N_C^T \\ C \end{bmatrix}, N_c \in \mathbb{R}^{n\times(n-p)} \text{ and columns span the null space of } C \qquad (4.6)$$

This is a nonsingular transformation and the transformed matrices are defined as:

$$T_c A T_c^{-1} = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}, T_c B = \begin{bmatrix} B_1 \\ B_2 \end{bmatrix}, C T_c^{-1} = [0 \quad I_p] \qquad (4.7)$$

Using the above transformation on system (4.1), we get:

$$\begin{aligned} \dot{\psi}(t) &= A_{11,j(t)}\psi(t) + A_{12,j(t)}y(t) \\ \dot{y}(t) &= A_{21,j(t)}\psi(t) + A_{22,j(t)}y(t) \end{aligned} \qquad (4.8)$$

where

$$T_c A_{j(t)} T_c^{-1} = \begin{bmatrix} A_{11,j(t)} & A_{12,j(t)} \\ A_{21,j(t)} & A_{22,j(t)} \end{bmatrix} \qquad (4.9)$$

The observer stack for (4.8) is defined as:

$$\begin{aligned} \dot{\hat{\psi}}_i(t) &= A_{11,\mathrm{i}}\hat{\psi}_i(t) + A_{12,i}\hat{y}_i(t) + L_i\nu_i(t), i = \{1, 2, ..., m\} \\ \dot{\hat{y}}_i(t) &= A_{21,i}\hat{\psi}_i(t) + A_{22,i}\hat{y}_i(t) - \nu_i(t) \end{aligned} \qquad (4.10)$$

where

$L_i \in \mathbb{R}^{(n-p)\times p}$ are the observer gain matrices and

$\nu_i \in \mathbb{R}^p$ is the discontinuous injection term that ensures the sliding motion and is designed as:

$$\begin{aligned}&\nu_i = K\mathrm{sign}(e_{y,i}(t)),\ i = \{1,2,...,m\}\\&\mathrm{Re}\left\{\sigma_j\left\{A_{11,i} + L_i A_{21,i}\right\}\right\} \le -\gamma, \forall j = 1,2,...,n-p, \gamma > 0, i = \{1,2,....,m\}\end{aligned} \tag{4.11}$$

where

$$\begin{aligned}&K \in \mathbb{R}^+\\&e_{y,i} = \hat{y}_i - y,\ i\{1,2,...,m\}\end{aligned} \tag{4.12}$$

and

$\sigma_j(N),\ j = 1,2,...,n$ for a square matrix N of order n denotes the set of corresponding real eigenvalues.

Assumption 3: The sub-matrices $A_{21,i}$ are not full row rank $\forall i = 1,2,....,m$.

A slightly modified form of Theorem 3 of [30] for identifying the discrete modes is given below.

Theorem 4.1: Let us consider the switched linear system (4.1), fulfilling Assumptions 1, 2 and 3, and the observer stack (4.10). Let an estimate $\hat{\nu}_{eq,i}(t)$ be available then the discrete state estimation

$$\hat{j}(t) = \arg\min_i R_i(t), R_i(t) = \int_{t-\tau}^{t} \left\|\bar{\hat{\nu}}_{eq,i}(\tau)\right\| d\tau, i = 1,2,...,m \tag{4.13}$$

will be such that

$$\hat{j}(t) = j(t),\ t_{k-1} + T^* \le t \le t_k,\ \mathrm{k} = 1, 2, \ldots \tag{4.14}$$

where

$\bar{\hat{v}}_{eq,i}(t) = U_i^T \hat{v}_{eq,i}(t), U_i$ is the basis matrix of the left null space of $A_{21,i}$ for $i = \{1, 2, \ldots, m\}$ and $\dot{\hat{v}}_{eq,i}(t) = K\left(v_i(t) - \hat{v}_{eq,i}(t)\right)$

The proof of the observer convergence and above theorem can be seen in [30].

The estimated continuous states of the SLS are then discretized by using a discretizer function defined as:

Definition 4.2

When jth mode is active, discretizer function f maps the continuous state of the system to a discrete state *s* belonging to M_c i.e.

$$s = f_j(x) \text{ .where } s \in M_c, x \in \mathbb{R}^n \tag{4.15}$$

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

$$s = f_j(x) = \begin{cases} j+m & x(t)-h \ge \varepsilon,\ \ j \in M \\ j & x(t)-h < \varepsilon,\ \ j \in M \end{cases} \quad . \tag{4.16}$$

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

In the next step, these symbols are converted in the string to be used at the input of the proposed DFA. A DFA is a Finite State Machine (FSM) that accepts or rejects finite strings of symbols [88]. FSM is a way of modeling system behavior with finite number of states [87]. In addition to its vast applications in the computer technology, it was applied for modeling, analysis and fault diagnosis of the hybrid systems by both computer science and control community [89], [90], [91], [92]. In the design process of the proposed DFA, the states of the DFA are assigned to ensure the validity of the input string sequence. A separate state sequence is kept in the DFA to identify each possible valid string. In the proposed FDI scheme for the SLS, the string acceptance or rejection property of the DFA is exploited for the processing of the identified modes in developing a systematic way of monitoring mode sequence for the fault detection and isolation. This systematic monitoring of mode sequence enables us not only in the immediate detection and isolation of faults but also facilitates in finding the involved dynamics (whether continuous or discrete) of the hybrid systems. This is achieved by designing a DFA in such a way as its states immediately detect and isolate the faulty component in the SLS and at the same time indicates the cause of the fault whether it occurred due to the continuous behavior or is reflected in the discrete evolution trajectory.

The proposed DFA is formally defined as a 5-tuple [88], [93].

$$D = \left(Q, \Sigma, \delta, q_0, F_s\right). \tag{4.17}$$

where

Q $=$ Set of states

Σ $=$ Set of symbols called alphabet

$\delta : Q \times \Sigma \rightarrow Q$ $=$ Transition function

q_0 $=$ Initial state

F_s $=$ Final state

We define a regular language **F** recognized by the DFA. This language consists of the strings formed through symbols generated by using (4.16). For a SLS with m subsystems we define $2m$ symbols (m symbols corresponding to the healthy subsystems and m symbols corresponding to their faulty behavior). Thus the alphabet in this case becomes as:

$$\Sigma = \{1, 2, ..., 2m\} = M_c \,. \tag{4.18}$$

and

$$\text{F=}\left\{\begin{array}{c}\text{Set of strings over } \Sigma\text{/each string} \\ \text{corresponds to specific fault}\end{array}\right\}. \tag{4.19}$$

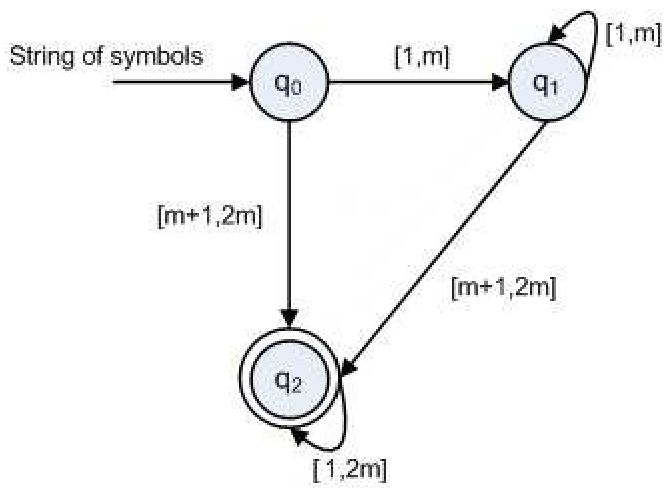

Figure-4.1 General structure of the proposed DFA

Figure-4.1 gives a general representation of the proposed DFA. This figure shows that this DFA has three states; q_0 is the start state, q_1 is the state indicating healthy system and q_2 is the desired or accepted state indicated by double circle. The transition between states occurs depending upon the input string. For a string containing symbols corresponding to the healthy system the transition occurs to the state q_1. Similarly the presence of any symbol corresponding to the faulty system forces the system to transition to q_2. It should be noted that the real applications can involve more states of the DFA than presented in the Figure-4.1 i.e. for each subsystem we can have two states; one indicating its healthy behavior and the other is for faulty behavior. Also note that the DFA of Figure-4.1 can be useful only in the applications involving the detection of faults reflected in the continuous states. However it provides the advantage of simplicity and easy implementation.

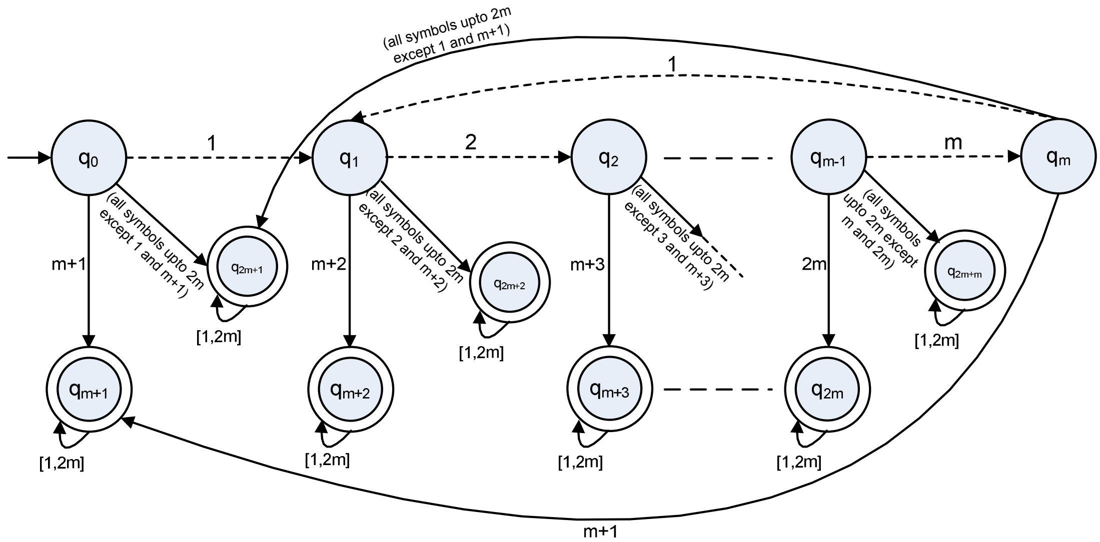

Figure-4.2 General structure of the proposed DFA for the fault detection and isolation

For the detection as well isolation of faults and to find about the nature of the dynamics involved in the fault occurrence, we have to add more states in the DFA. This is shown in the Figure-4.2 that assumes the healthy mode sequence as 1, 2, …, *m*. Moreover, new faults can be diagnosed by using additional states in the designed DFA. The number of states in the DFA of Figure-4.2 is equal to $3m+1$ i.e. $Q = \{q_0, q_1, ..., q_{3m}\}$, where q_0 is the start state, $\{q_1, q_2, ..., q_m\}$ correspond to the healthy modes, $\{q_{m+1}, q_{m+2}, ..., q_{2m}\}$ correspond to the faulty modes of the hybrid system corresponding to the continuous states and $\{q_{2m+1}, q_{2m+2}, ..., q_{3m}\}$ represents the faulty modes corresponding to the discrete states. The transition between the DFA states is governed by (4.19) and (4.20) given below.

$$H = \left\{ \begin{array}{l} \text{Set of strings over } \Sigma \text{/each string represnts a sequence} \\ \text{corresponding to healthy system} \end{array} \right\} \tag{4.20}$$

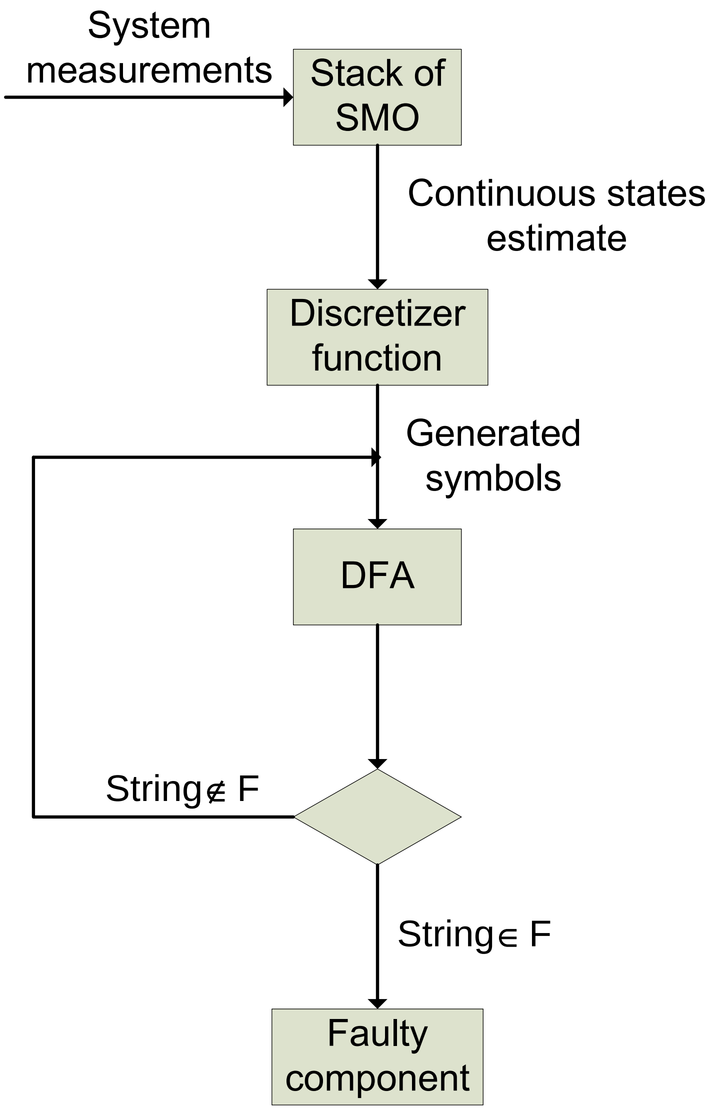

Figure-4.3 Proposed methodology for the FDI of SLS

For healthy operation of the system, the transition occurs only between the DFA states corresponding to the healthy modes and is based upon (4.20). This path is represented by the dotted arrows in the Figure-4.2. The transition among healthy and faulty states is governed by (4.19). The occurrence of any symbol in a sequence corresponding to the faulty mode results in the corresponding "accepted state" of the DFA represented by the double circle in the Figure-4.2, thus detecting and isolating this fault. The switching from healthy modes to the faulty modes representing faults reflecting in discrete states can be described in the similar way. This transition, however, can also occur in the presence of a symbol representing the healthy mode of the system depending upon its sequence.

The complete FDI scheme is summarized in the Figure-4.3. In the next Section, a simulation example is presented to explain the above presented FDI scheme.

4.3 Simulation example

This Section gives the simulation example to illustrate the effectiveness of our proposed scheme. For this purpose, the switched linear system given in [30] is taken as a benchmark system and is described as below:

$$\begin{aligned} \dot{x}(t) &= A_{j(t)}x(t) \\ y(t) &= Cx(t) \end{aligned} \tag{4.21}$$

This system has two modes i.e. $m = 2$, thus $j(t) \in \{1, 2\}$ with $A_{j(t)}$ as given below

$$A_1 = \begin{bmatrix} 0 & 0.6 & -1 \\ -0.5 & -0.8 & 1 \\ 0.1 & 0.4 & -0.7 \end{bmatrix}, A_2 = \begin{bmatrix} 0 & 0.3 & -0.8 \\ -1 & -0.4 & 0.8 \\ 1 & 0.6 & -0.3 \end{bmatrix} \tag{4.22}$$

so (4.3) becomes as:

$$M = \{1, 2\}, \bar{M} = \{3, 4\} \text{ and } M_c = \{1, 2, 3, 4\} \tag{4.23}$$

Output matrix C is given as:

$$C = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \tag{4.24}$$

The initial conditions are taken as $x_0 = \begin{bmatrix} -3 & -1 & 6 \end{bmatrix}^T$. The system starts with mode A_1 and the switching times are defined as $t_k = \{8, 14, 20, 24\}$. To transform the system in new coordinates, (4.6) becomes as

$$T_c = \begin{bmatrix} 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \tag{4.25}$$

So the system in new coordinates becomes as

$$\begin{bmatrix} \dot{\psi}(t) \\ \dot{y}(t) \end{bmatrix} = \begin{bmatrix} A_{11,j(t)} & A_{12,j(t)} \\ A_{21,j(t)} & A_{22,j(t)} \end{bmatrix} \begin{bmatrix} \psi(t) \\ y(t) \end{bmatrix} \tag{4.26}$$

with

$$A_{11,1} = -0.7, A_{12,1} = [0.1 \;\; 0.4], A_{21,1} = [-1 \;\; 1]^T, A_{22,1} = \begin{bmatrix} 0 & 0.6 \\ -0.5 & -0.8 \end{bmatrix} \tag{4.27}$$

and

$$A_{11,2} = -0.3, A_{12,2} = [1 \;\; 0.6], A_{21,2} = [-0.8 \;\; 0.8]^T, A_{22,2} = \begin{bmatrix} 0 & 0.3 \\ -1 & -0.4 \end{bmatrix} \tag{4.28}$$

Figure-4.4 presents the simulation results of the nominal system described by (4.27) and (4.28). The observer stack is defined according to (4.10) and L_i and K are chosen as defined in (4.11) and (4.12). The sliding surface is designed in terms of tracking error and corresponds to the subspace where output error is zero:

$$e_{y,i} = \hat{y}_i - y = 0, \ \ i = \{1, 2, ..., m\} \tag{4.29}$$

The residuals for the mode identification are generated according to the (4.13) and are shown in this figure. The estimated active modes are also plotted in this figure that provides the information of the active mode on the corresponding switching times. The estimated state x_3 is shown in the Figure-4.5.

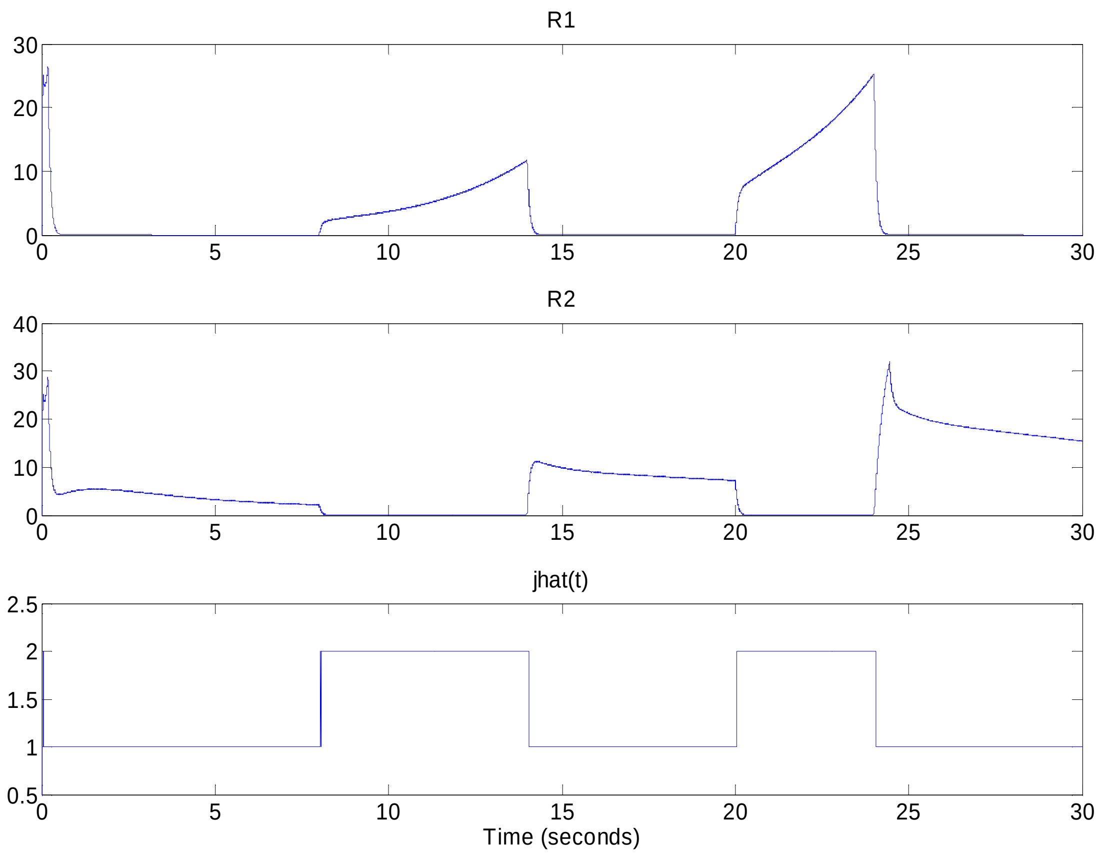

Figure-4.4 Residuals for mode identification and estimated modes

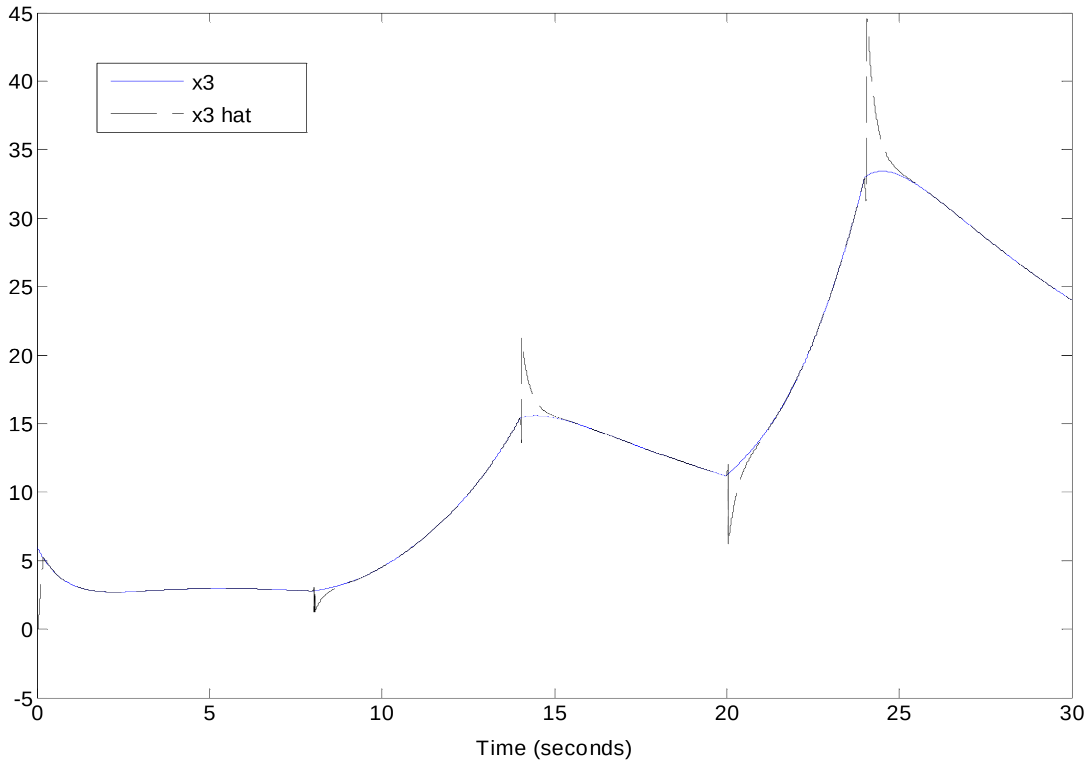

Figure-4.5 Actual vs estimated state

Introducing a fault in the first subsystem of (4.21), at time $t = 4 \text{ to } 7$ seconds as $\bar{a}_{12,1} = (1-\delta)a_{12,1}$, $\delta = 0.5$, we get the following

$$\begin{bmatrix} \dot{\psi}_f(t) \\ \dot{y}_f(t) \end{bmatrix} = \begin{bmatrix} \bar{A}_{11,p(t)} & \bar{A}_{12,p(t)} \\ \bar{A}_{21,p(t)} & \bar{A}_{22,p(t)} \end{bmatrix} \begin{bmatrix} \psi_f(t) \\ y_f(t) \end{bmatrix} \tag{4.30}$$

with

$$\bar{A}_{11,1} = -0.7, \bar{A}_{12,1} = [0.1 \quad 0.4], \bar{A}_{21,1} = [-1 \quad 1]^T, \bar{A}_{22,1} = \begin{bmatrix} 0 & 0.3 \\ -0.5 & -0.8 \end{bmatrix} \tag{4.31}$$

The faulty system is simulated and the residuals for the mode identification and the estimated modes are shown in the Figure-4.6. The error between desired state for the nominal system and the same state for the faulty system is shown in the Figure-4.7, from which we find using (4.16) that the system switches into new mode (faulty mode) m=3. Using Figure-4.2, the DFA for this example can be designed as presented in the Figure-4.8. This DFA has $3m+1=7$ states. The alphabet $\sum$ becomes in this case as:

$$\sum = M_c = \{1,2,3,4\} \qquad (4.32)$$

The DFA states q_1, q_2 represent the healthy operation of the system, the states q_3, q_4 represent the fault in the continuous states of the system and the states q_5, q_6 correspond to the modes representing the faults reflected in the discrete states of the system. In the fault case mentioned above, the DFA of the Figure-4.8 switches to the state q_3 thus detecting and isolating the fault.

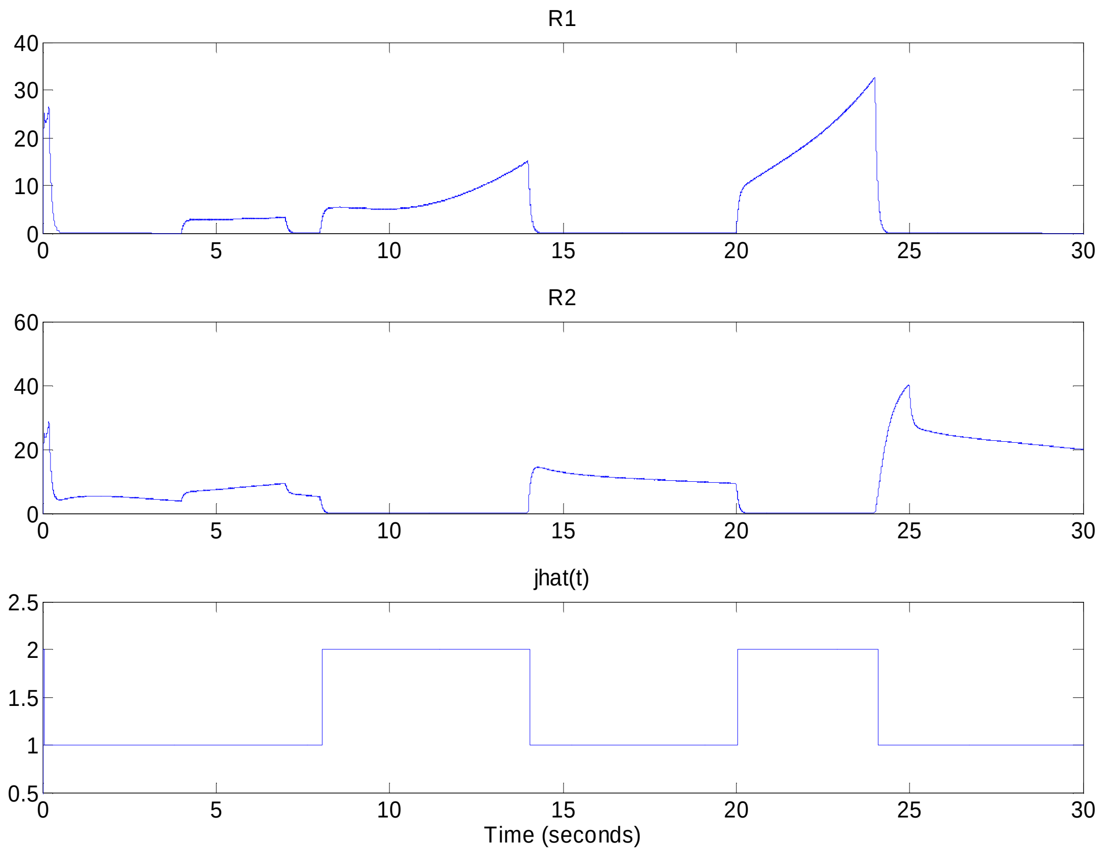

Figure-4.6 Residuals for mode identification and estimated modes for faulty system

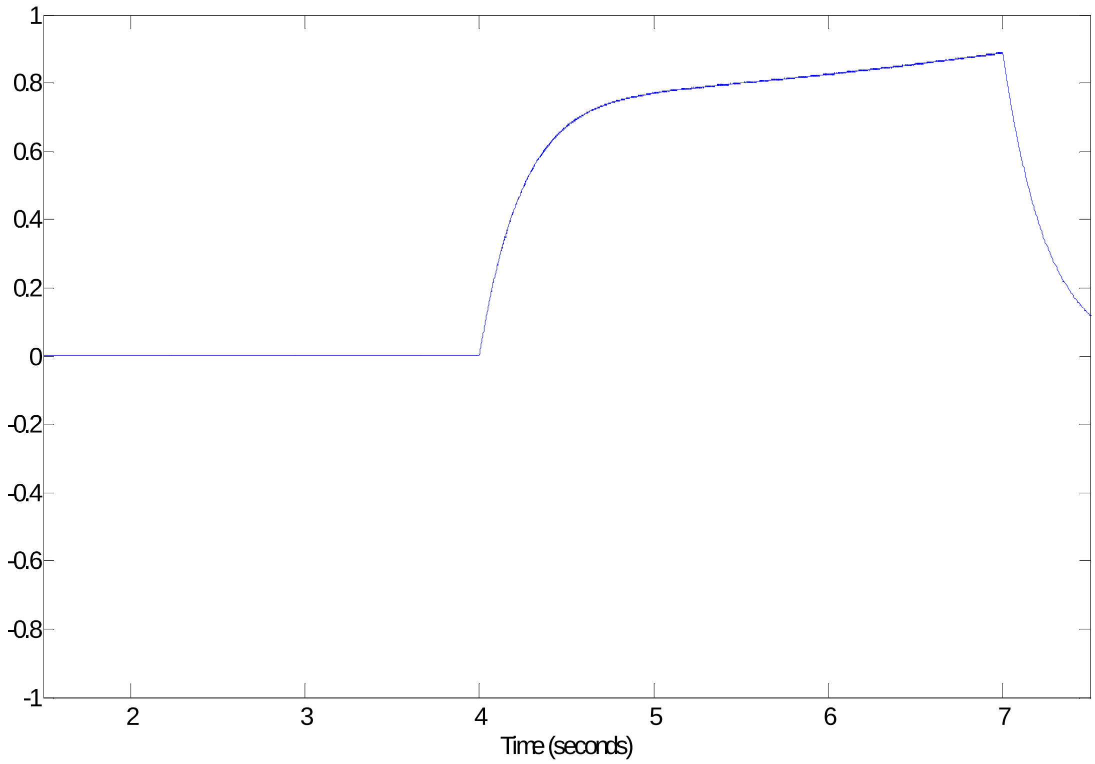

Figure-4.7 Error between desired state and faulty system state

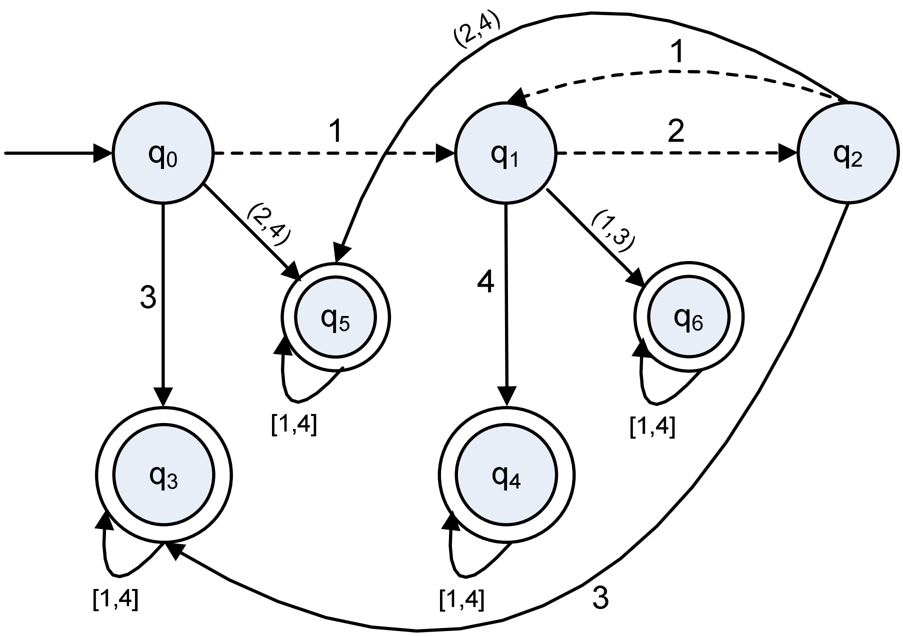

Figure-4.8 DFA for simulation example

Next consider that the fault in the system (4.21) that are modelled by an incorrect order of discrete modes. In this case the system does not follow the desired switching sequence mentioned in the start of this Section. This fault is introduced by vanishing the switching at t=8 sec. In real world systems such faults can occur when the system stuck in a particular mode e.g. due to the jamming of a valve etc. The residuals for the mode identification and the estimated modes for the presented case are shown in the Figure-4.9 from which it can be seen that the switching at time instant t=8 sec is missing. Note that this type of fault too can cause the (4.16) to generate a symbol that can be used to indicate the fault due to the continuous dynamics of the hybrid system, but our designed DFA recognizes this case also and switches to the correct state even in these cases (see Figure-4.8). For the present case, the DFA of Figure-4.8 switches from q_1 to q_6 , thus detecting and isolating the fault.

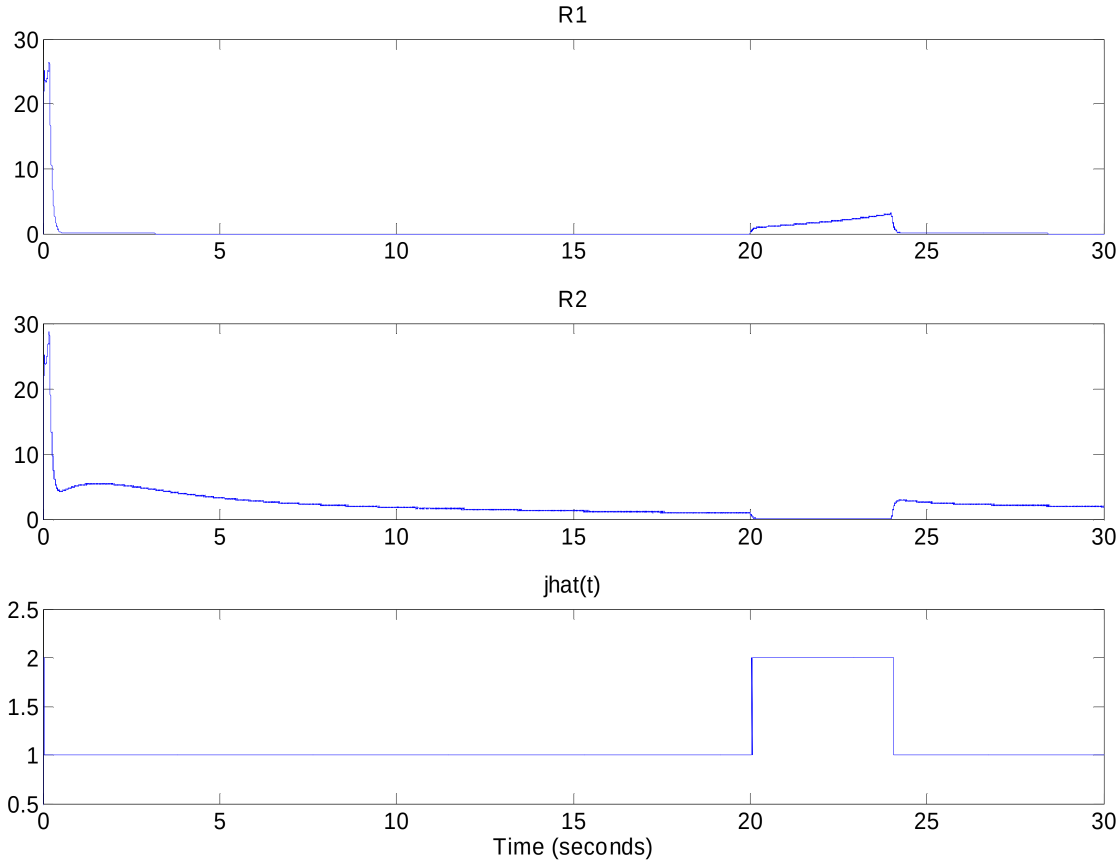

Figure-4.9 Residuals for mode identification and estimated modes for faulty system

A similar robust state estimation based fault diagnosis technique is presented in [78] for the uncertain hybrid systems where faults are modelled in terms of discrete modes. As compared to our proposed technique, the approach presented in [78] requires a dedicated observer scheme for mode estimation and a separate observer scheme for continuous estimation. These observers consist of bank of Unknown Input Extended Kalman Filter (UIEKF). As mentioned earlier Kalman filter is a recursive technique and requires more computations in the estimation process as compared to the SMO that is a computationally economical for online implementations. Moreover in [78] robustness to the disturbances and model uncertainties is achieved through decoupling technique thus further increasing the computational complexity. In contrast to this, SMO used in our proposed scheme is inherently a robust technique and does not require additional computations for achieving robustness to disturbances and model uncertainties. Furthermore the time taken in the mode estimation process by the approach of [78] is quite high as compared to the SMO approach adopted by us that provides the mode estimate almost instantly (see Figure-4.4, Figure-4.5 and Figure-4.6). Another issue is that, in [78] fault detection is performed only for the continuous faults of the hybrid system and discrete faults are not addressed while in our proposed FDI technique we used the estimated modes in diagnosing both the discrete and continuous faults of the system using the same scheme.

4.4 Summary

This chapter presented a FDI scheme for an important class of the hybrid systems known as Switched Linear Systems. The presented scheme estimates the system states using SMO and performs the mode identification for FDI based on the analysis of these states. A DFA is designed that analyze the mode sequence for the FDI purpose. These identified modes, represented as symbols of a language acceptable to the proposed DFA, acts as the DFA input. The proposed FDI scheme directly detects and identifies the faults in the SLS and also indicates the involved dynamics in the fault process. New faults can be easily diagnosed by adding the new strings to a fault set **F** and using additional states in the DFA.

The proposed technique is successfully validated through simulations and the results are presented. Being a model-based FDI technique the proposed scheme is simple and easy to implement for the practical purposes. Moreover the use of SMO ensures the robustness in the state estimation process.

CHAPTER 5

MODE IDENTIFICATION SCHEME FOR THE FDI OF SLS – PART II

In this chapter, we enhance the mode identification scheme for the FDI of the SLS presented in the previous chapter. The presented scheme removes the need for state estimation and analysis used in the symbol generation process but at the cost of additional SMO stacks. These symbols representing system modes appear at the input of a DFA that processes them in search of a fault. New faults can be detected and isolated by introducing new strings. The proposed algorithm is applied to a switched linear model of the SI engine for the misfire fault detection and the results for simulations and experimental data are presented.

This chapter starts with an introduction to the proposed scheme. Section 5.2 describes the proposed FDI scheme. Section 5.3 demonstrates the application of the proposed scheme on the SI engine and Section 5.4 concludes the whole work.

5.1 Introduction

The FDI approach presented in the previous chapter estimates the system states and use them in the mode identification process that are analyzed by the DFA for the fault detection and isolation. The use of the SMO in the state estimation process provides several advantages over the approaches using Kalman filter, as mentioned in the previous chapter. However, the proposed approach has a limitation in the FDI process for the switched systems having identical subsystems. An example of such systems is the SI engine that consists of four identical cylinders that actuate sequentially on the corresponding events. From the FDI perspective, in this chapter a new mode identification scheme is proposed for such systems. The proposed scheme uses additional SMO stacks, each one of which represents a mode and captures a specific fault reflected in the continuous dynamics. This approach also simplifies the symbol generation process of the previous chapter by removing the need for state estimation and analysis process. Moreover, the number of the DFA states is also reduced as compared to the approach presented in the previous chapter.

The proposed FDI technique monitors the mode sequence in the FDI process. A DFA is designed for the analysis of mode sequences used in the detection and isolation of fault. The DFA takes the identified modes as the input, represented as the symbol of a language acceptable to that DFA. The proposed algorithm starts with the formation of the SMO stacks and used these to generate the symbols for the DFA.

5.2 The proposed scheme

Consider a switched linear system with m identical subsystems represented as:

$$\begin{aligned} \dot{x}(t) &= A_{j(t)}x(t) \\ y(t) &= Cx(t) \end{aligned} \tag{5.1}$$

where $x(t) \in \mathbb{R}^n$ represents the state vector, $y(t) \in \mathbb{R}^p$ represents the output vector, and $j(t) \in M = \{1, 2, ..., m\}$ determines the active system dynamics among the m possible subsystems.

In case of healthy system, all subsystems of the SLS *(5.1)* are working in the normal way and a system behavior can be obtained using nominal system model and/or knowledge about system operation. In case of fault, the system behavior deviates from that of the nominal one and can be generated for various faults using system model and knowledge in a similar way. The SMO stacks can be designed to track these behaviors of the SLS by taking each faulty situation as a new switched system. This approach also takes care of the SLS with identical, out of phase subsystems as will be shown in the Section 5.3.

For the present case, we assume only a single fault is related to a subsystem. Moreover, only one subsystem can be faulty at a time and no fault is assumed to occur at switching times.

The faulty systems are represented as:

$$
\begin{aligned}
&\dot{x}_f(t) = \bar{A}_{\lambda(t)} x_f(t) \\
&y_f(t) = C x_f(t), \quad \lambda(t) \in \{m+1, 2, 3, ..., m\} \\
\\
&\dot{x}_f(t) = \bar{A}_{\lambda(t)} x_f(t) \\
&y_f(t) = C x_f(t), \quad \lambda(t) \in \{1, m+2, 3, ..., m\} \\
&\qquad\qquad\qquad \vdots \\
&\qquad\qquad\qquad \vdots \\
&\dot{x}_f(t) = \bar{A}_{\lambda(t)} x_f(t) \\
&y_f(t) = C x_f(t), \quad \lambda(t) \in \{1, 2, ..., m-1, 2m\}
\end{aligned}
\tag{5.2}
$$

where $\bar{M} = \{m+1, m+2, ..., 2m\}$ is an index set for m possible faulty subsystems such that:

$$
M_c = M \cup \bar{M} \tag{5.3}
$$

For the symbol generation, we design stacks of SMOs for each of the system given in (5.2). The number of stacks used for the proposed scheme are $m+1$; one stack for the nominal system (5.1) and m stacks for the systems given in (5.2). So transforming the (5.1) in the new coordinates as in (4.8) and designing first stack of SMOs, we get the following:

$$
\begin{aligned}
\dot{\psi}(t) &= A_{11,\lambda(t)} \psi(t) + A_{12,\lambda(t)} y(t) \\
\dot{y}(t) &= A_{21,\lambda(t)} \psi(t) + A_{22,\lambda(t)} y(t)
\end{aligned}
\tag{5.4}
$$

with

$$\begin{bmatrix} \psi \\ y \end{bmatrix} = T_c x \tag{5.5}$$

The observer stack for (5.4) is defined as:

$$\begin{aligned} \dot{\hat{\psi}}_i(t) &= A_{11,i}\hat{\psi}_i(t) + A_{12,i}\hat{y}_i(t) + L_i\nu_i(t), i = \{1, 2, ..., m\} \\ \dot{\hat{y}}_i(t) &= A_{21,i}\hat{\psi}_i(t) + A_{22,i}\hat{y}_i(t) - \nu_i(t) \end{aligned} \tag{5.6}$$

where

$L_i \in \mathbb{R}^{(n-p)\times p}$ and $\nu_i \in \mathbb{R}^p$ are defined as in Section 4.2.

Similarly, the systems in (5.2) are transformed in the new coordinates and the observer stacks are defined as:

$$\begin{aligned} &\dot{\hat{\psi}}_i(t) = A_{11,i}\hat{\psi}_i(t) + A_{12,i}\hat{y}_i(t) + L_i\nu_i(t), i = \{1, 2, ..., m\}, && \text{(based on system 5.2 with} \\ &\dot{\hat{y}}_i(t) = A_{21,i}\hat{\psi}_i(t) + A_{22,i}\hat{y}_i(t) - \nu_i(t) && \lambda(t) \in \{m+1, 2, ..., m\}) \\ &\qquad\vdots \\ &\qquad\vdots \\ &\dot{\hat{\psi}}_i(t) = A_{11,i}\hat{\psi}_i(t) + A_{12,i}\hat{y}_i(t) + L_i\nu_i(t), i = \{1, 2, ..., m\}, && \text{(based on system 5.2 with} \\ &\dot{\hat{y}}_i(t) = A_{21,i}\hat{\psi}_i(t) + A_{22,i}\hat{y}_i(t) - \nu_i(t) && \lambda(t) \in \{1, 2, ..., m-1, 2m\}) \end{aligned}$$

(5.7)

These stacks are used to track the output of the system for generating the symbols representing the system modes, and are indexed using an index set as $s(t) \in S = \{s_1, s_2, ..., s_{m+1}\}$. The process of symbol generation using these stacks is performed as:

$$s(t) = s_p, p = \arg e_l(t) \to 0, e_l(t) = \hat{y}_l(t) - y(t), l = \{1, 2, ..., m+1\} \tag{5.8}$$

For the cases when $e_l(t) \neq 0 \ \forall l = \{1, 2, ..., m+1\}$, the p is replaced with $m+2$.

In the next step, a DFA similar to that of Chapter 4 is designed to develop a systematic way of monitoring mode sequence for the fault detection and isolation. This designed DFA, however, provides the advantage of simplicity for involving less number of states.

A regular language **F**, recognized by the designed DFA, is defined. This language consists of the strings formed through symbols generated by u g (5.8). For a SLS with m subsystems we define $m+2$ symbols (m symbols corresponding to (5.7), one symbol corresponding to the healthy operation and one corresponding to the faulty operation reflected as unknown fault). Thus the alphabet Σ in this case becomes as:

$$\Sigma = \{s_1, s_2, ..., s_{m+2}\}. \tag{5.9}$$

and

$$\text{F}=\left\{\begin{matrix}\text{Set of strings over } \Sigma\text{/each string} \\ \text{corresponds to specific fault}\end{matrix}\right\}. \tag{5.10}$$

Figure-5.1 gives a general representation of the proposed DFA. This figure shows that this DFA has $m+3$ states; q_0 is the start state, q_1 is the state indicating healthy system, $q_2, ..., q_{m+1} (m \text{ states})$ represent desired or accepted states (indicated by double circle in the Figure-5.1) and corresponds to the faults reflected in the continuous states of the system and q_{m+2} is the state indicating unknown faults. The transition between states occurs depending upon the input string. For a string containing symbols corresponding to the healthy system the transition occurs to the state q_1. Similarly the presence of any symbol corresponding to the faulty system forces the system to transfer to one of the $q_2, ..., q_{m+2}$. The detailed interpretation of Figure-5.1 can be done as already given in Section 4.2.

Figure-5.2 gives the summary of the complete FDI technique. The proposed FDI scheme is validated both through simulations and the experimental results using switched linear model of a SI engine. The next Section presents the application of the proposed FDI scheme on the hybrid model of the SI engine and results are presented in the later Section.

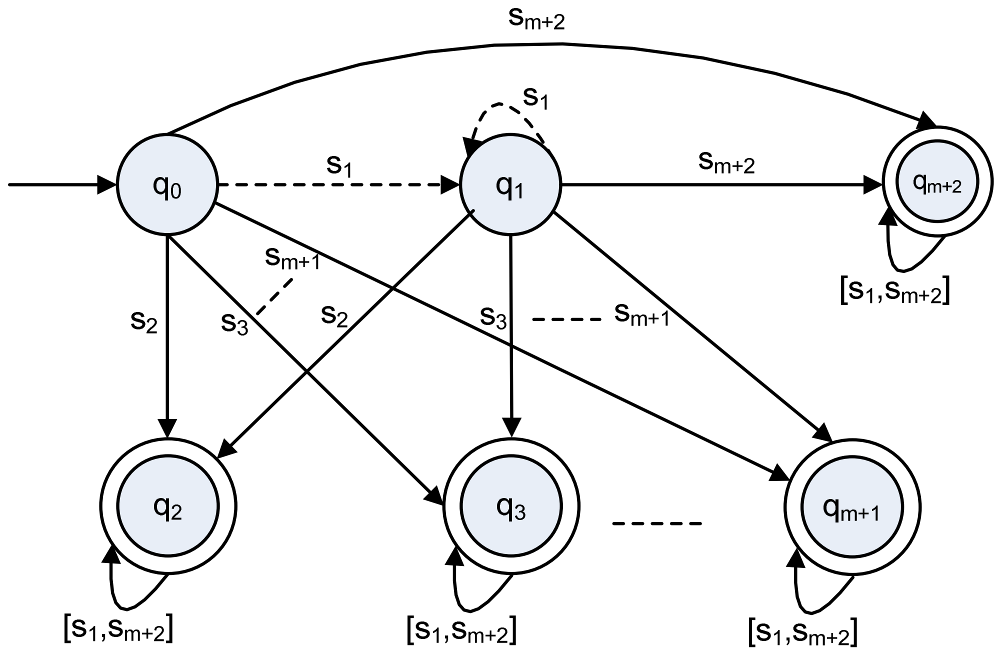

Figure-5.1 General structure of the proposed DFA

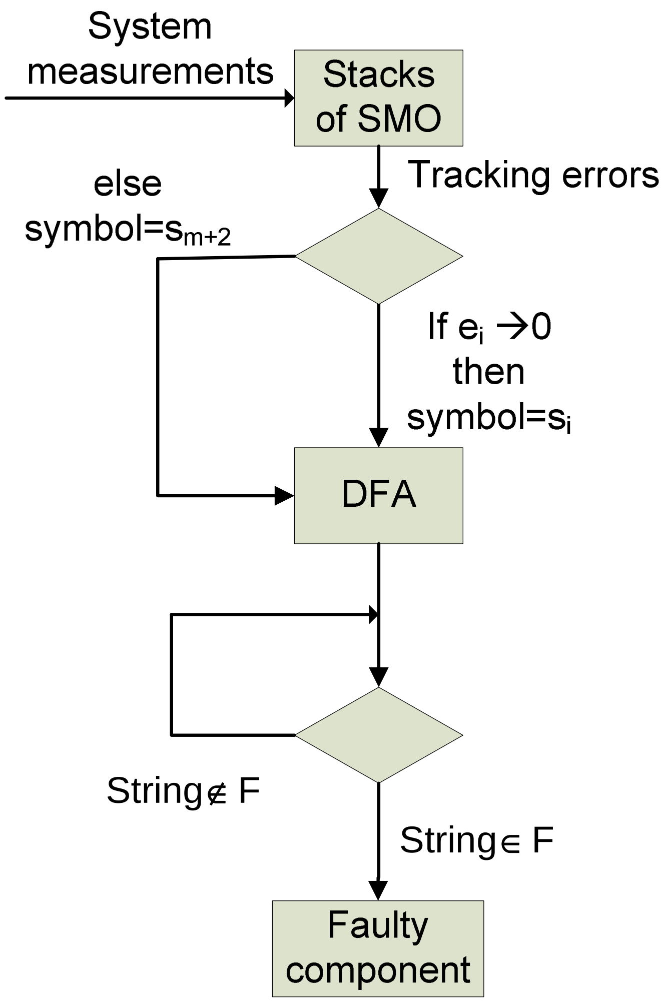

Figure-5.2 Proposed methodology for the FDI of SLS

5.3 An application example

This Section describes the application of the proposed FDI scheme on a real world system with identical subsystems. The proposed mode identification scheme for the FDI of the SLS is applied on a SI engine modeled as a switched linear system. The scheme is successfully applied to detect the misfire fault in the SI engine. This engine contains four cylinders coupled together through a single shaft to transmit engine power to the wheels. These cylinders are represented as subsystems of a switched linear engine model. Thus here

$$M = \{1, 2, 3, 4\} \tag{5.11}$$

and

$$\bar{M} = \{5, 6, 7, 8\} \tag{5.12}$$

so (5.3) becomes

$$M_c = \{1, 2, \ldots, 8\} \tag{5.13}$$

Under ideal conditions all subsystems are assumed to be identical and are working in fault-free mode. A predefined correct ignition sequence in cylinders ensures the healthy operation of the SI engine. The sequences other than this predefined sequence will indicate faulty engine operation. In the current demonstration, misfire fault is introduced in the engine to produce the faulty engine operation. This disturbs the correct ignition sequence as the ignition of misfiring cylinder is missing and no power is generated in the misfiring cylinder.

The model of the SI engine used here for the observer design is the switched linear model proposed in [94] and is described in the following sub-section.

5.3.1 Hybrid model of SI engine

Before explaining the hybrid model of the SI engine, a brief description of the engine ignition cycle is presented to introduce the terminology used in the sequel. SI engines are based on the Otto cycle that takes four independent strokes of the piston for completion. These are given below:

- Intake stroke
- Compression Stroke
- Power Stroke
- Exhaust Stroke

The intake stroke starts with the piston at Top Dead Center (TDC). The input port opens and the output port remains closed. Air from intake manifold is sucked in the cylinder by piston motion from TDC to Bottom Dead Center (BDC).

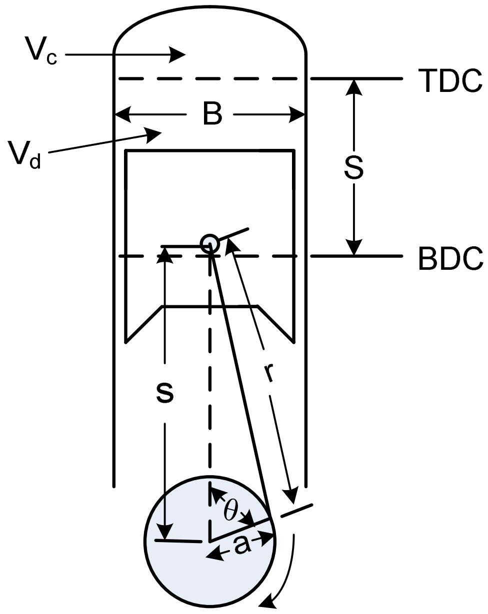

Figure-5.3 Engine cylinder [95]

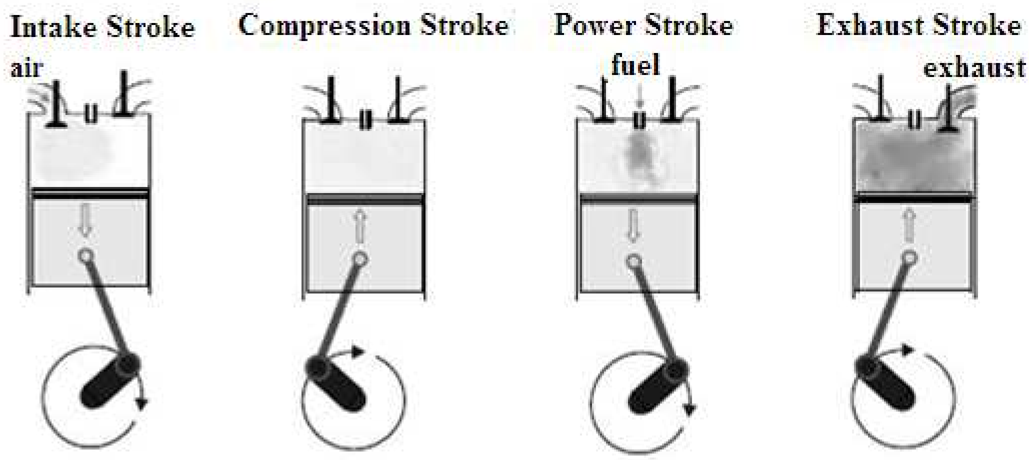

Figure-5.4 SI engine ignition cycle [96]

In the compression stroke the piston moves from BDC to TDC. Both the input and output ports are closed. This is an isentropic compression and the temperature inside cylinder rises due to the compressive heating.

In the power stroke the heat is added to the system. The process is assumed to be constant volume process but in actual engine heat addition starts when the piston reaches just before the TDC and ends when it is just after TDC. The temperature of the air inside cylinder rises to very high values. This also causes high pressure in the cylinder that result in piston motion from TDC to BDC. The energy added in this stroke is divided in three parts; one part is utilized in useful work in moving the piston from TDC to BDC, second part is transferred to the coolant and the third part resides in the cylinder in the form of hot gases.

In the exhaust stroke the remaining gases in the cylinder after power stroke are exhausted to the environment through engine exhaust. The output port of the cylinder opens and piston moves from BDC to TDC resulting in the sweeping out of exhaust gases.

Figure-5.3 gives the engine cylinder along with the relevant terms used in the ignition cycle and Figure-5.4 gives the four strokes described above with the corresponding piston position in these strokes.

The SI engine hybrid model used in this work represents a four cylinder engine. It is a switched linear hybrid model in which each cylinder of the SI engine is considered as a subsystem. These cylinders activate one by one on their respective events i.e. only one of the cylinder will be in the power stroke at a particular time instant. The remaining cylinders will be in one of the intake, compression and exhaust stroke, depending upon the ignition cycle. In this model, just power stroke of the cylinders is considered. On completion of the power stroke of one cylinder, it switches to the next cylinder. This switching is state dependent switching and is a deterministic process.

The hybrid model of the SI engine captures the steady state behavior of the engine in which only small fluctuations exists in the crankshaft speed. Moreover, due to the frequent switching between subsystems, the model validation time is very less and thus each subsystem can be assumed to be represented as linear time invariant model. For overall system, the output is the combined effect of all the subsystems.

Mathematically, the hybrid model of the SI engine is defined as a 5-tuple model $<\mu, X, \Gamma, \sum_e, \phi>$ in [94]. For our proposed FDI technique, we modify this model to include fault states as well.

$$M_c = \mu = M \cup \overline{M} \tag{5.14}$$

where terms are already explained in (5.11) to (5.13)

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

$\Gamma = \{G\}$ is a singleton for a maximally balanced engine, where G represents mathematical model of all subsystems as state space model. The state space models for the subsystems are derived on the first principle basis as in [94] that proposed a second order system for the subsystems of the hybrid model of an SI engine. The elements of the set Γ contain the equivalent state space representation of the model defined as:

$$\begin{aligned} \dot{x} &= A_l x + Bu \\ y &= Cx \end{aligned} . \tag{5.15}$$

where

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

$\sum_e : \mu \rightarrow \mu$ represents the generator function used to define the next transition model.

$\phi : \Gamma \times \mu \times X \times u \rightarrow X$ 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.

5.3.2 Application on SI engine

Each subsystem in SI model described above is represented as second order system given below.

$$\begin{aligned} \dot{v}_{1,j} &= v_2 \\ \dot{v}_{2,j} &= -k_{2,j} v_{2,j} - k_{1,j} v_{1,j} + aP_j , \qquad j \in \{1,2,3,4\} \end{aligned} . \tag{5.16}$$

For application of the SMO stack, the observability of the pair (A_i, C) for $\mathrm{i} = 1,2,3,4$ can be seen as

$$\mathrm{rank}(O_i) = 2, \text{ where } O_i = \begin{bmatrix} C \\ CA_i \\ \vdots \\ CA_i^{n-1} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{5.17}$$

Using transformation (4.6), (5.16) is transformed in new coordinates as

$$\begin{aligned} \dot{\psi}(t) &= -k_{2,j}\psi(t) - k_{1,j}y(t) + aP_j \\ \dot{y}(t) &= \psi(t) \end{aligned}. \tag{5.18}$$

with

$$T_c = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}. \tag{5.19}$$

$m+1$ observer stacks defined in (5.6) and (5.7) becomes as

$$\begin{aligned}
&\dot{\hat{\psi}}_i(t) = -k_{2,i}\hat{\psi}_i(t) - k_{1,i}\hat{y}_i(t) + aP_i + L_i\nu_i(t),\ i = \{1,2,...,m\} \\
&\dot{\hat{y}}_i(t) = \hat{\psi}_i(t) - \nu_i(\mathrm{t}) \\
&\dot{\hat{\psi}}_i(t) = A_{11,i}\hat{\psi}_i(t) + A_{12,i}\hat{y}_i(t) + aP_i + L_i\nu_i(t),\ i = \{1,2,...,m\} \\
&\dot{\hat{y}}_i(t) = A_{21,i}\hat{\psi}_i(t) + A_{22,i}\hat{y}_i(t) - \nu_i(\mathrm{t}),\ (\text{based on system with } \lambda(t) \in \{m+1,2,...,m\}) \\
&\qquad\qquad\vdots \\
&\qquad\qquad\vdots \\
&\dot{\hat{\psi}}_i(t) = A_{11,i}\hat{\psi}_i(t) + A_{12,i}\hat{y}_i(t) + aP_i + L_i\nu_i(t),\ i = \{1,2,...,m\} \\
&\dot{\hat{y}}_i(t) = A_{21,i}\hat{\psi}_i(t) + A_{22,i}\hat{y}_i(t) - \nu_i(\mathrm{t}),\ (\text{based on system with } \lambda(t) \in \{1,2,...,m-1,2m\})
\end{aligned}$$

. (5.20)

Using (5.9), the alphabet for SI engine is defined as

$$\sum = \{s_1, s_2, ..., s_6\}. \tag{5.21}$$

The SMO stacks are then used for the mode identification (see Section 5.3.3 and 5.3.4), which are represented as symbols of the language acceptable to the DFA. The DFA designed for this particular example is shown in Figure-5.5. The transition between the DFA states takes place based on the symbols present in the DFA input string and can be interpreted in the same way as in the previous chapter. We can see that this DFA has 7 states with q_0 as the start state. The presence of the system in any of states q_2, q_3, q_4, q_5 indicates the fault reflected in the continuous states of the engine. The unknown faults can be given by the system presence in the states q_6.

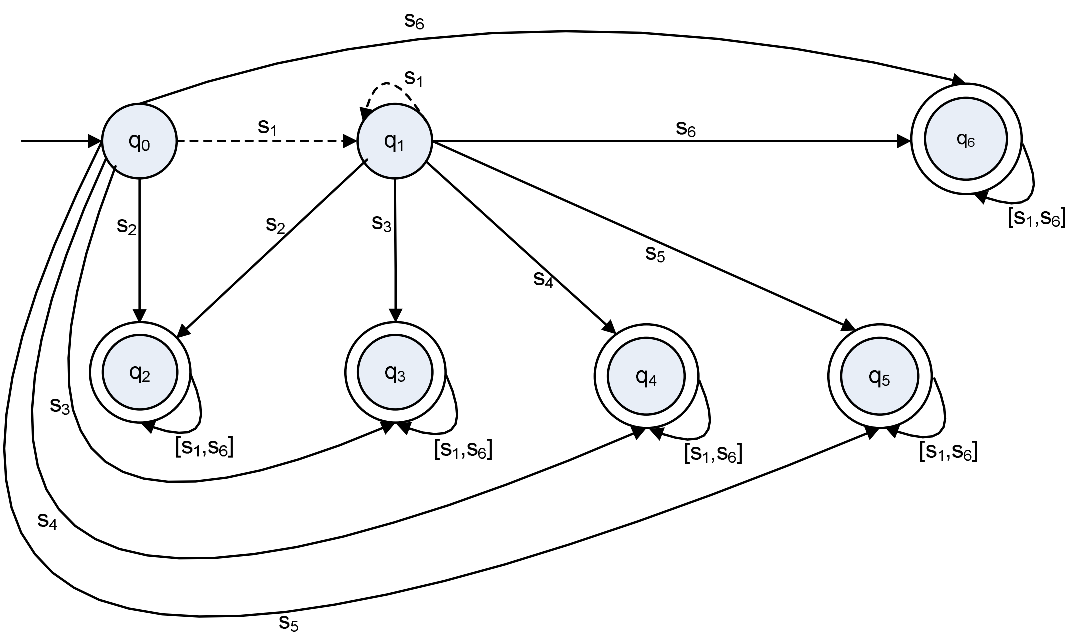

Figure-5.5 DFA for the application example

5.3.3 Simulation results

In this Section, we describe the simulation results for both the healthy and faulty cases. The switched linear model of SI is parameterized as in [94] and then it is simulated in the first step for fault-free case. Later on, the process is repeated with the misfire introduced in the engine model.

The crankshaft speed data for the healthy engine is shown in the Figure-5.6. In the first stage, this speed profile is provided to the SMO stacks as inputs. The resulting tracking errors are shown in the Figure-5.7. Using (5.8), it can be clearly seen from Figure-5.7 that the generated symbol is s_1 in this case that results in the q_1 state of the DFA of the Figure-5.5, thus indicating healthy behaviour of the system.

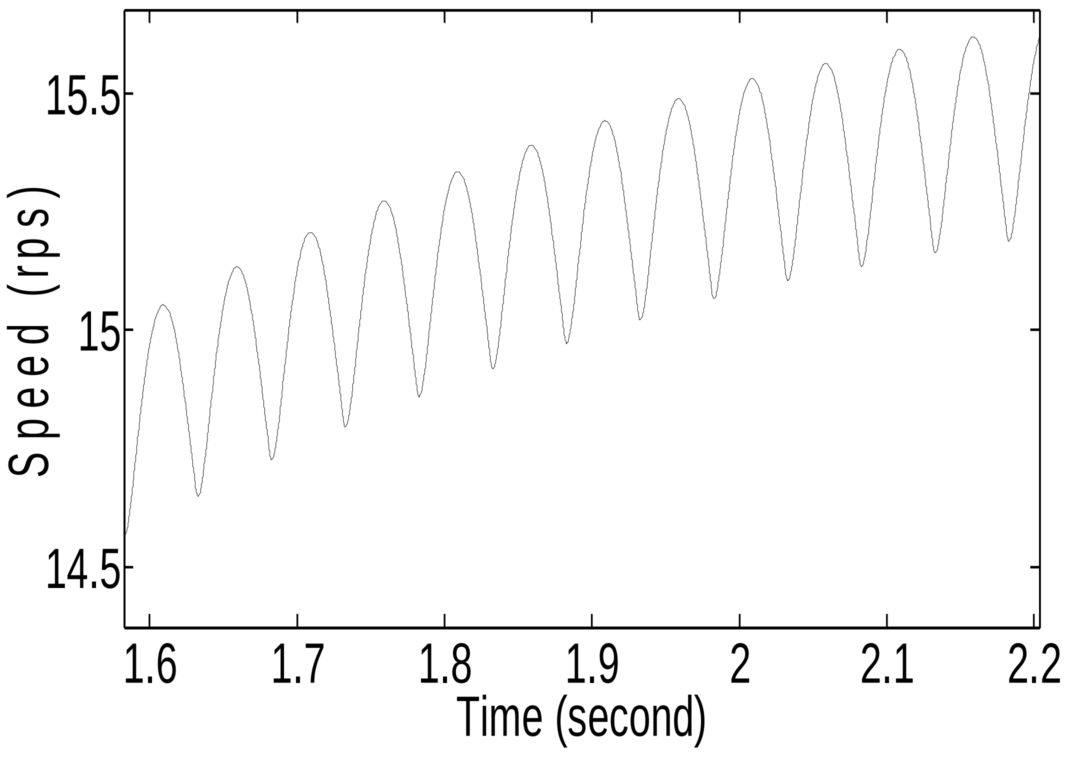

Figure-5.6 Crankshaft speed for fault-free case

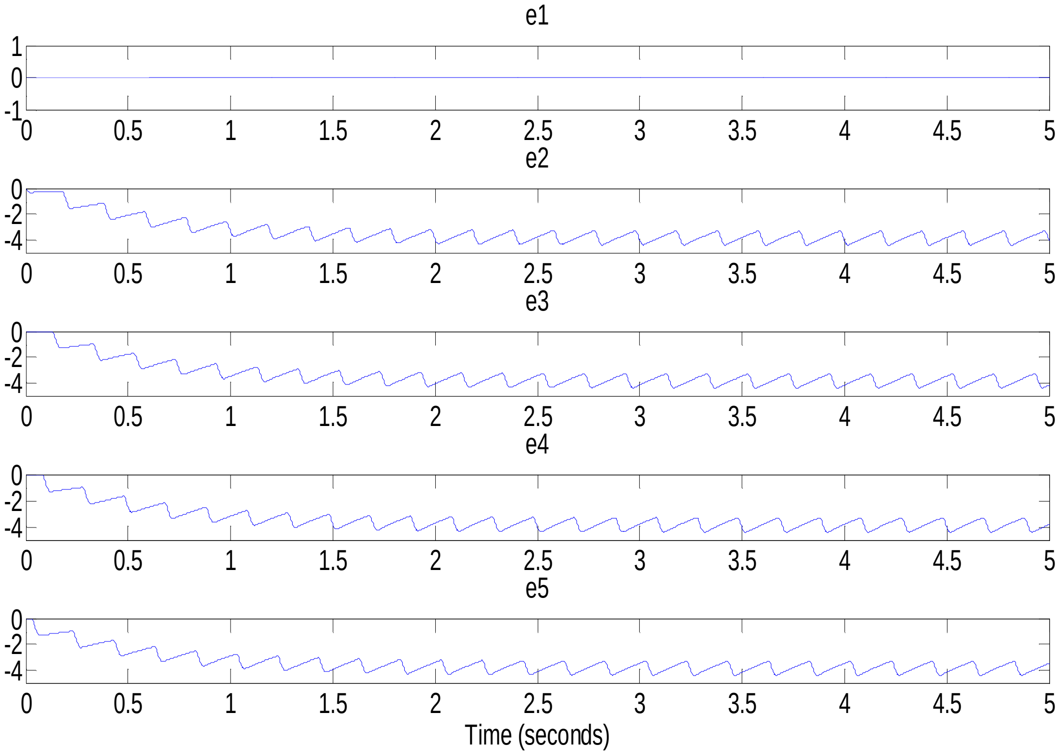

Figure-5.7 SMO stacks error plots for fault-free case

Figure-5.8 presents the crankshaft speed data for the misfire fault in the SI engine. This speed profile is provided to the SMO stacks as input and the resulting error plots are shown in the Figure-5.9, from which it can be seen that the generated symbol is s_2 that results in the q_2 of the DFA of the Figure-5.5, thus detecting and isolating the fault.

From these simulation results, the effectiveness of the proposed scheme is evident in detection and isolation of faults in the SLSs. The next Section gives the experimental validation of these results.

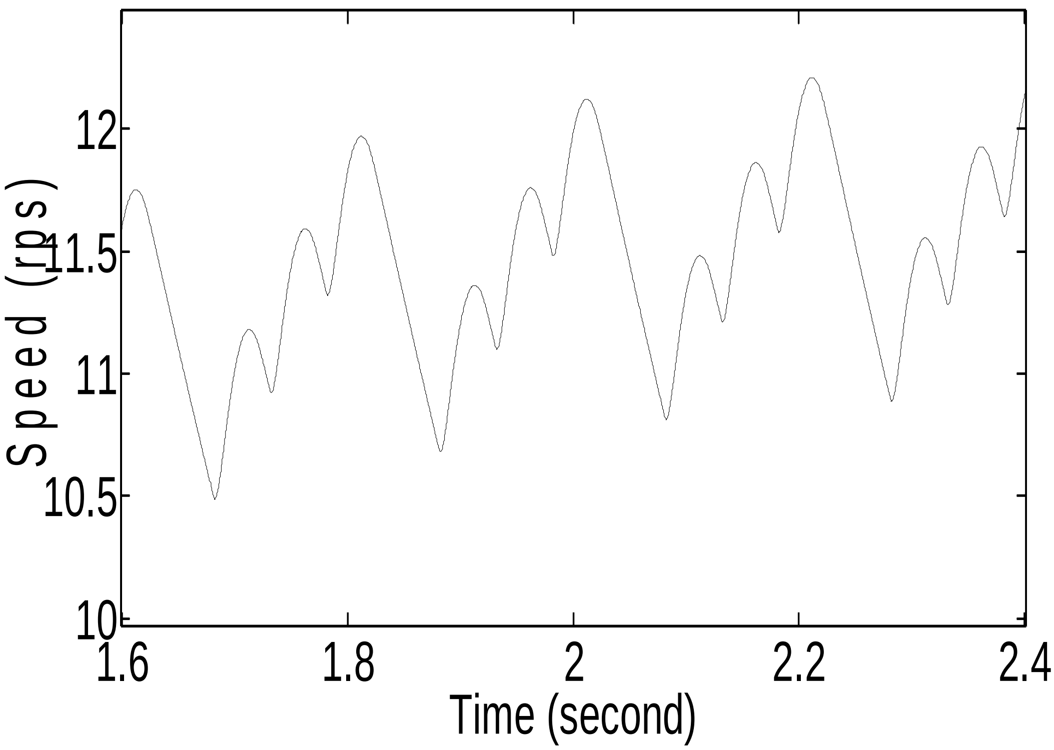

Figure-5.8 Crankshaft speed for misfire fault in cylinder 1

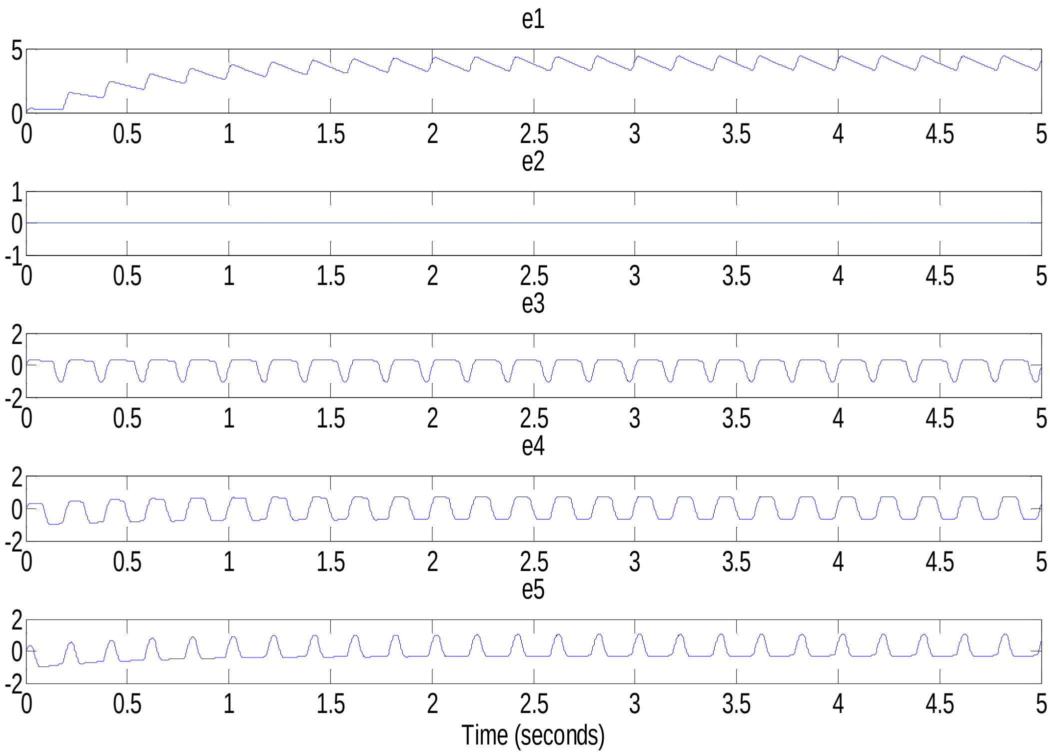

Figure-5.9 SMO stacks error plots for misfire in first cylinder

5.3.4 Experimental results

This Section gives the description of the experimental setup along with the results used to validate the proposed FDI scheme. First of all we describe the experimental set up used for the work presented in this dissertation. Data for the validation of the proposed scheme is acquired from an engine rig of 1.3L production vehicle compliant with the On-Board Diagnostic II (OBD-II). This is shown in Figure-5.10. This engine is equipped with the Electronic Control Unit (ECU) compliant to the OBD-II standards.

We can acquire data from this experimental setup using either of the following:

- Using the National Instrument (NI) data acquisition card connected directly to the vehicle sensors. LabVIEW is the software used in this process. (Figure-5.11)
- By using the OBD-II connector provided in the vehicle. In this method an OBD-II cable is used to connect an OBD-II scanner to the OBD-II connector to acquire the sensors data. (Figure-5.12)

Figure-5.10 Engine rig of 1.3 L production vehicle

Figure-5.11 NI card used for data acquisition

Figure-5.12 Data acquisition through OBD-II connector

During the experiments, misfire fault is introduced by removing one spark circuit. (Figure-5.13)

Figure-5.13 Misfire fault production

The experimental rig is also equipped with wheels and brakes. During the data acquisition process, the wheels of the rig were raised in the air to stop its movement and brakes were used to apply load on the engine. The crankshaft speed is kept close to 1000 rpm by the manual control of throttle and brakes. This manual control of the speed and load also added disturbances in the acquired data. Moreover, the working environment of the engine is always noisy due to the factors like EMI interference of igniter coil, combustion process in engine cylinders and engine vibrations etc. These all factors also effect the data acquisition from the engine. This noisy data was supplied to the proposed algorithm to ascertain its ruggedness for the practical noisy signals.

Data from the crankshaft position sensor is acquired using data acquisition card from the National Instrument Inc. This data was processed to obtain the crankshaft speed signal that is applied to the observer after appropriate filtering using a low pass filter. In the next stage, misfire fault is introduced in the 3^{rd} cylinder of the SI engine by inhibiting the igniter signal to the engine. The same process is repeated again and the speed data is acquired for the misfire case.

Figure-5.14 shows the filtered signals of the speed obtained from the experimental measurements for the fault-free case. The resulting tracking errors are shown in the

Figure-5.15 indicating that the generated symbol is s_1 in this case, which results in the q_1 state of the DFA of the Figure-5.5.

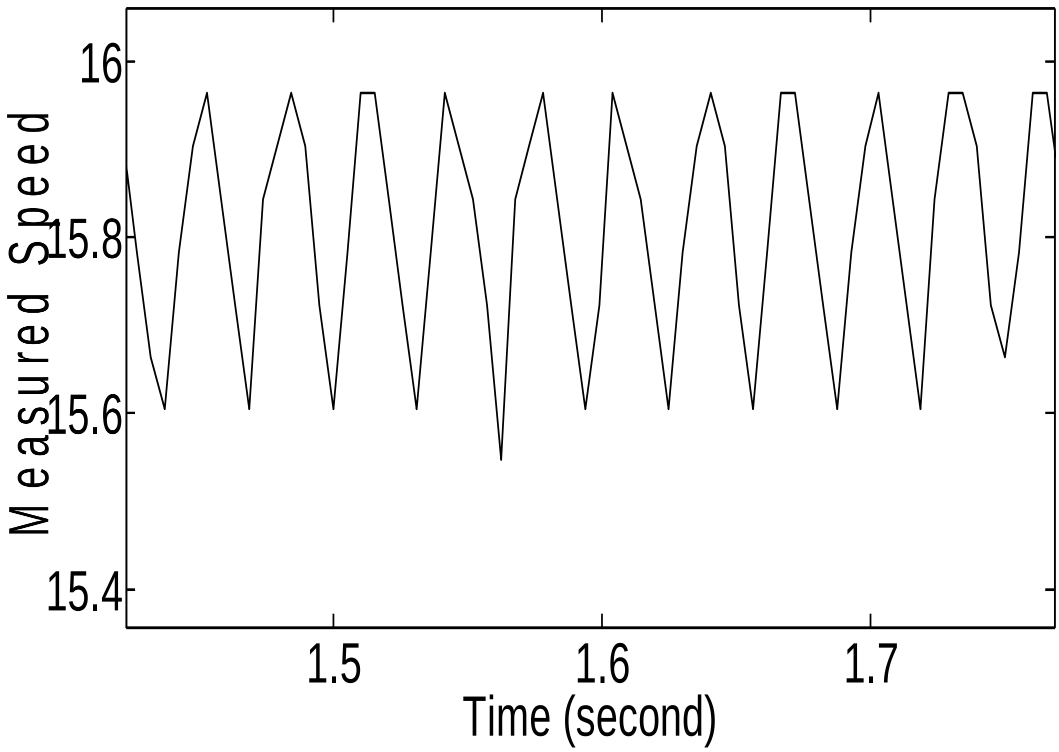

Figure-5.14 Crankshaft speed measurement for fault-free case

Figure-5.16 presents the speed signal with the misfire fault in the third cylinder. Figure-5.17 presents the resulting tracking errors of the SMO stacks. The analysis of these error plots using (5.8) implies that the generated symbol in this case is s_4, that results in the q_4 state of the DFA of the Figure-5.5, thus detecting and isolating the fault.

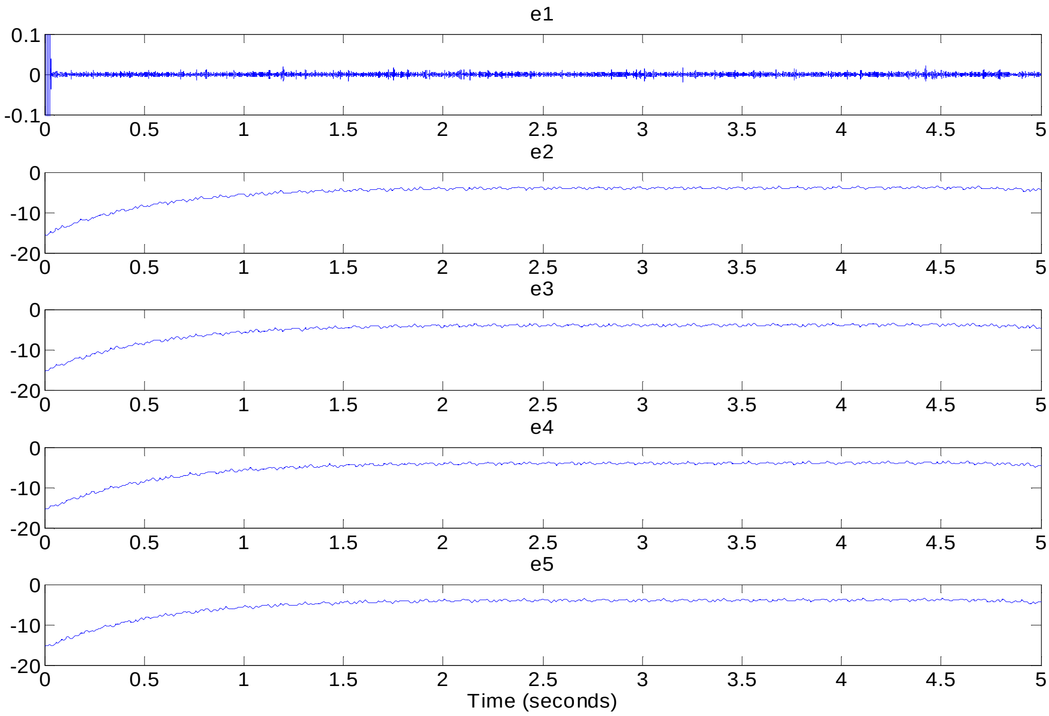

Figure-5.15 SMO stacks error plots for fault-free case

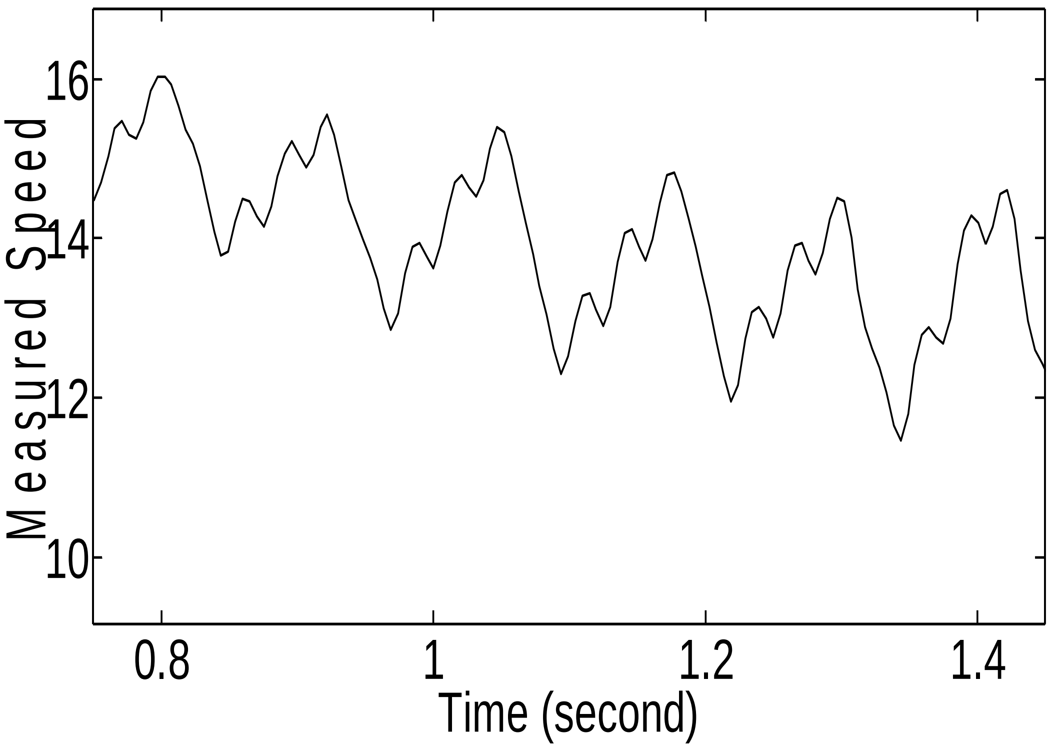

Figure-5.16 Crankshaft speed measurement for misfire fault in cylinder 3

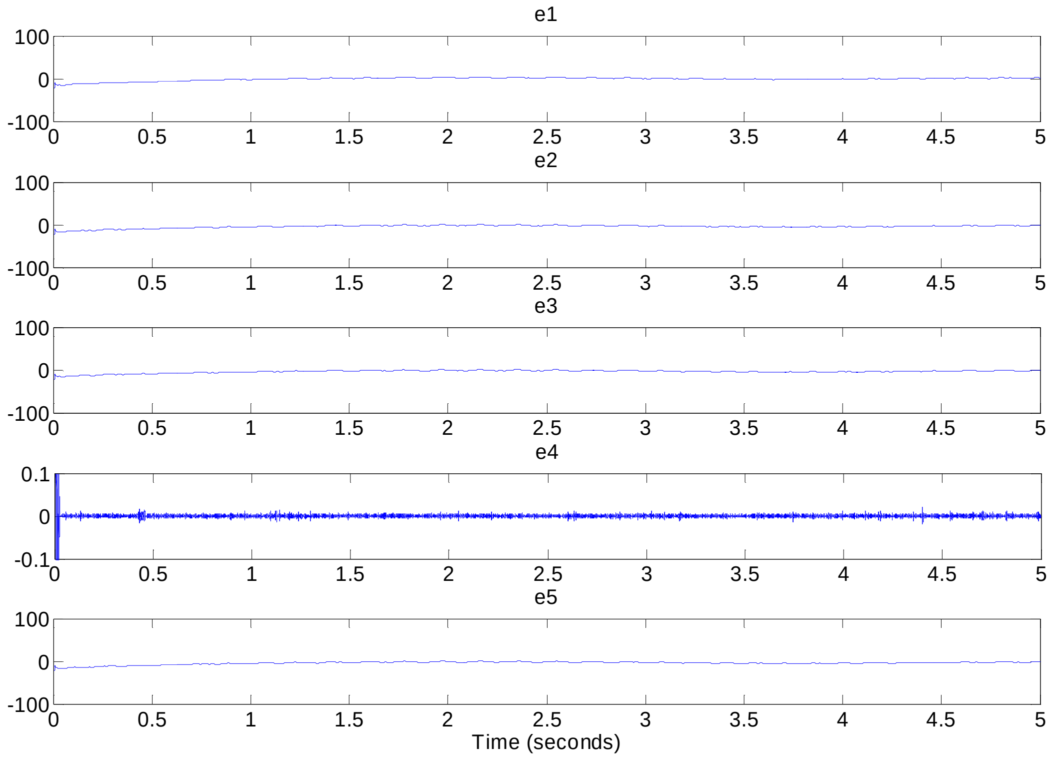

Figure-5.17 SMO stacks error plots for misfire in cylinder 3

The representation of a highly nonlinear SI engine using a switched linear hybrid model provides quite simpler tracking technique using the SMO. The model also provides an easy way for the association of the modes with the complex non-linear system and the proposed technique demonstrates the application how the mode identification and the allowable mode sequence can be used for the fault diagnosis applications.

5.4 Summary

This chapter presented a mode identifications scheme for the FDI of the hybrid systems that can be equally applicable to the SLS with identical subsystems as well. The proposed scheme also eliminates the need of state estimation and analysis steps. Moreover, the designed DFA also contains fewer states as compared to the previous approach.

The scheme is successfully validated on a SI engine that has four identical cylinders, represented as the four subsystems in a switched linear model. The representation of a highly nonlinear SI engine as switched linear system allows the development of the simple FDI technique based on the definition and identification of the system modes.

CHAPTER 6

MODE IDENTIFICATION SCHEME FOR THE MISFIRE DETECTION IN SI ENGINE

This chapter demonstrates the use of the mode sequence monitoring in the FDI process by detecting and isolating the misfire fault in the SI engine. The work presented in this chapter is published in [26]. The engine setup available for the experimental purposes is a four cylinder 1.3L spark ignition engine. Using the hybrid model of the SI engine, a hybrid observer is defined where discrete event is identified and then the continuous model of the subsystem is selected for the design of observer using the sliding mode technique. The observer output is finally used for the mode identification and fault diagnosis.

This chapter starts with the introduction of the misfire fault in the SI engine. Section 6.2 gives the description of the hybrid model of the SI engine used in this work. Section 6.3 gives the detail of the proposed mode identification scheme for the FDI of the SI engine. Section 6.4 describes the simulation results and Section 6.5 is about the experimental results. Section 6.6 gives a comparison of the existing misfire detection approaches and the proposed approach. Section 6.7 gives a summary of this chapter.

6.1 Introduction

In the SI engine, the ignition of the air-fuel mixture in the engine cylinder produces energy used in generating torque. The combustion process involved in this process is initiated through a spark generated by a spark plug. In case of misfire fault, this combustion process is either missing or cannot be performed completely in the corresponding stroke of the engine ignition cycle. Engine misfire can be due to several reasons like missing spark, poor fuel injection, poor fuel quality, incorrect air-fuel mixture etc. Misfire fault is formally defined as fault due to missing spark, air leakage from cylinder or fault in the fuel injection [97]. There are several disadvantages related to this fault, few of them are listed below.

- Environmental pollution caused by exhausting unburned fuel
- Unable to produce required torque

- Damage to the catalytic convertor
- Bad fuel economy
- Low millage
- Uncomfortable travelling etc

The misfire problem was given a lot of attention by the scientific community in the past but new techniques are still being developed for the solution of this issue [94], [98], [99], [100], [101], [102], [103], [104], [105], [106], [107]. Variety of methods was adopted for the detection of the misfire fault including model-based techniques, data based techniques and a combination of both model-based and data based methods [94]. Model-based methods utilize the SI engine model for developing the misfire detection algorithm and can be easily implemented online as discussed earlier. The most frequently used model of the SI engine for parameter and state estimation using observer design is the Mean Value Engine Model (MVEM), as indicated by the literature [20], [21], [22], [23], [24]. This model is simple and less complex due to its averaging nature and thus is suitable for many control applications. However, the details skipped by the MVEM contain information useful for the fault diagnosis [12], [94]. Recently, hybrid models capturing more details of the SI engine are evolving for the fault diagnosis applications [12], [94]. These models indicate the potential of the hybrid model for the fault diagnosis applications that lead to the significant simplification due to the replacement of highly nonlinear engine dynamics with linear model for the estimation of states in all different modes.

In the proposed misfire detection scheme, we applied SMO on the engine hybrid model for the state estimation. These estimated state variables are analyzed for identifying the system modes for the FDI purpose. The identified modes are then monitored to detect the misfire fault in the SI engine. The presented misfire fault detection technique is simple and easy to implement online as it is computationally cheap involving only linear models, and being model-based technique it gives the physical insight of the origin of the misfire fault. Moreover the robust state estimates are provided by the SMO even in the presence of model uncertainties.

The next Section gives the details of the hybrid model used for the development of the proposed FDI scheme.

6.2 Hybrid model of SI engine

The hybrid model of the SI engine used in this thesis is adopted from [94] and is already discussed in Section 5.3.1. In this Section, this model is briefly discussed along with the modifications made in it for the present work.

Mathematically, the hybrid model of SI engine is defined as a 5-tuple model $<\mu, X, \Gamma, \sum_e, \phi>$ in [94]. For our proposed FDI technique, we modify this model to include fault states as well.

$$\Omega = \mu = \mu_H \cup \mu_F \ . \tag{6.1}$$

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 and Ω is the complete mode set.

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

$\Gamma = \{G\}$ is a singleton for a maximally balanced engine, where G represents mathematical model of all subsystems as state space model. The state space models for the subsystems are derived on the first principle basis as in [94]. The referenced model proposed a second order system for the subsystems of the hybrid model of an SI engine. The elements of the set Γ contain the equivalent state space representation of the model defined as:

$$\begin{aligned} \dot{x} &= A_l x + Bu \\ y &= Cx \end{aligned} \ . \tag{6.2}$$

where

$$u \in \mathbb{R}, A \in \mathbb{R}^{2\times2}, B \in \mathbb{R}^{2\times1}, C \in \mathbb{R}^{1\times2}, l \in \{1,2,3,4\}$$

$\sum_e : \mu \to \mu$ represents the generator function used to define the next transition model. In SI engine, during ignition cycle there is one to one correspondence between piston position and crankshaft position, so switching is defined in terms of the instantaneous shaft position θ_1 as:

$$For\ \mu_H\ \ \Sigma = \begin{cases} \mu_1 & 4n\pi \le \int \dot{\theta}_1 dt < (4n+1)\pi \\ \mu_2 & (4n+1)\pi \le \int \dot{\theta}_1 dt < (4n+2)\pi \\ \mu_3 & (4n+2)\pi \le \int \dot{\theta}_1 dt < (4n+3)\pi \\ \mu_4 & (4n+3)\pi \le \int \dot{\theta}_1 dt < (4n+4)\pi \end{cases} \tag{6.3}$$

$$For\ \mu_F\ \ \Sigma = \begin{cases} \mu_5 & 4n\pi \le \int \dot{\theta}_1 dt < (4n+1)\pi \\ \mu_6 & (4n+1)\pi \le \int \dot{\theta}_1 dt < (4n+2)\pi \\ \mu_7 & (4n+2)\pi \le \int \dot{\theta}_1 dt < (4n+3)\pi \\ \mu_8 & (4n+3)\pi \le \int \dot{\theta}_1 dt < (4n+4)\pi \end{cases} \tag{6.4}$$

where n=0,1,2,3….

During each stroke of the SI engine ignition cycle the crankshaft rotates by 180˚. One whole ignition cycle of the SI engine completes by an angular movement of 720˚ i.e. by two complete revolutions of crankshaft (see Figure-5.4 of Chapter 5). At a given time instant, the nature of combustion stroke in each cylinder of the SI engine is different from others i.e. if one cylinder is in intake stoke at a particular time, no other cylinder can be in this stroke at that time and they might be in one of the compression, power or exhaust stroke at that time.

$\phi : \Gamma \times \mu \times X \times u \to X$ 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.

In the next Section, the proposed FDI scheme for the misfire detection is given.

6.3 The proposed scheme

The proposed FDI technique exploits the fact that deviation of mode sequence from that of expected can be used for the fault diagnosis [12]. We start with some definitions that will be used in this chapter.

Mode Sequence Estimation Function (MSEF)

It uses the output of the discretizer function and information of active subsystem i as its arguments and estimates the next mode appearing in the sequence.

$$p = g(j,i),\ p \in \Omega . \tag{6.5}$$

where the discretizer function is defined in (4.15) and for the SI engine it becomes as:

$$j = f_k(x) \text{ .where } j \in \Omega, x \in \mathbb{R}^2 \tag{6.6}$$

Switching Sequence

Switching sequence S associated with switched systems is indexed by the initial state x_0 and is given as [45]:

$$S = x_0;\ (i_0,t_0),(i_1,t_1),\ldots,(i_{2q},t_{2q}),\ldots. \tag{6.7}$$

6.3.1 Mode identification of SI engine

In our present work, healthy/faulty modes correspond to the actual production/non-production of the power in the cylinders due to the burning of air fuel mixture. The corresponding healthy and faulty modes are mutually disjoint at any instant. Therefore

$$\mu_H \cap \mu_F = 0\,. \tag{6.8}$$

In other words, the system must be in only one mode, healthy or faulty, at a particular time instant.

For the FDI purpose, the modes are identified by estimating and analyzing continuous states of the system. In SI engine misfire fault detection, the estimation of the continuous state is physically motivated as at the start of the power stroke of healthy engine the piston is accelerated inside a cylinder by the energy produced in the combustion process of the air-fuel mixture. The piston starts to decelerate in the later part of the power stroke. When a misfire fault event occurs in the engine, then no energy is produced in the cylinder to accelerate the piston and it continues to decelerate. As a result, large peak of deceleration are produced in this process [101], which corresponds to the faulty mode in this case. So acceleration can be analyzed for identifying healthy and faulty modes, which can be monitored for the FDI purpose. Unfortunately there is no acceleration sensor present in the production vehicle with SI engine. So to use it for the mode identification, we have to estimate it using an observer. For this purpose a FOSMO is designed. This observer is based on the hybrid model of the SI engine described in Section 6.2. It uses crankshaft speed as input and provides the estimate of the crankshaft acceleration. As discussed earlier, the use of SMO for state estimation comes with the benefit of robustness against model uncertainties and switching discontinuities. So we get robust and reliable estimates of states even under uncertain environment. Furthermore, it makes simple and easy online implementation of the designed scheme. The block diagram of the hybrid observer is shown in Figure 6.1.

Each subsystem in Figure 6.1 is represented as a second order system given below [94].

$$\begin{aligned} \dot{v}_{i1} &= v_{i2} \\ \dot{v}_{i2} &= -k_{i2} v_{i2} - k_{i1} v_{i1} + aP \quad, i = 1,2,3,4 \end{aligned}\,. \tag{6.9}$$

where

v_1 represents the crankshaft velocity

v_2 represents the crankshaft acceleration

a is a constant

P is the power generated in the cylinder

k_1 is elasticity coefficient

k_2 is friction coefficient

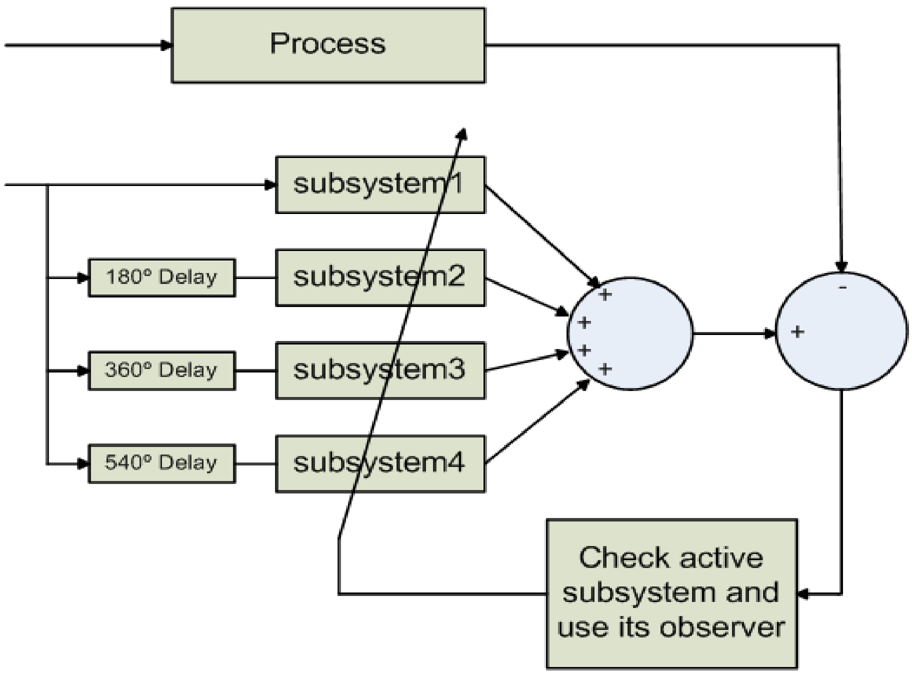

Figure-6.1 Structure of hybrid observer

Under ideal conditions, it is assumed that all the subsystems are identical and working in the healthy mode. A FOSMO is designed for the estimation of the crankshaft acceleration. The index *i* is dropped in the observer design for notational simplicity.

$$\begin{aligned}\dot{\hat{v}}_1 &= \hat{v}_2 + K_1\text{sign}(e_1)\\ \dot{\hat{v}}_2 &= -k_2\hat{v}_2 - k_1\hat{v}_1 + K_2\text{sign}(e_1) + aP\end{aligned}. \tag{6.10}$$

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

The function sign(.) is defined as:

$$\operatorname{sign}(e_1) = \begin{cases} +1 \text{ when } e_1 > 0 \\ -1 \text{ when } e_1 < 0 \end{cases}. \tag{6.11}$$

The error dynamics are obtained from (6.9) and (6.10), and are given as follows:

$$\begin{aligned} \dot{e}_1 &= e_2 - K_1 \operatorname{sign}(e_1) \\ \dot{e}_2 &= -k_2 e_2 - k_1 e_1 - K_2 \operatorname{sign}(e_1) \end{aligned}. \tag{6.12}$$

The convergence of the estimated state to the actual state is ensured by finding the stability of the error dynamics. Below we give the stability analysis of the error dynamics given in (6.12).

Stability Analysis

For the stability of the error dynamics, we consider a Lyapunov function of the form $V = \frac{1}{2} e_1^2$. For convergence $\dot{V} < 0$, so we have

$$\begin{aligned} \dot{V} &= \frac{1}{2} 2 e_1 \dot{e}_1 \\ &= e_1 (e_2 - K_1 \operatorname{sign}(e_1)) \end{aligned} \tag{6.13}$$

As e_1 is taken as switching surface, so from (6.13) we can find $K_1 > e_2$ for $\dot{V} < 0$.

Next we consider a result on the existence of the CLF from [43], [108] that show that the CLF exists for the switched system if all the subsystems commute pair-wise. So using the assumption of identical subsystems, the corresponding Lie bracket becomes as:

$$\left[f_i, f_j \right] = 0, \forall i, j \in \{1, 2, 3, 4\} \tag{6.14}$$

(6.13) and (6.14) imply that a CLF exists for this system. So using the work of [43], if a CLF exists for all the subsystems of a switched system then the switched dynamics is stable for an arbitrary switching sequence. The error dynamics of the hybrid observer are thus stable and convergence of the estimated states to the actual states is guaranteed.■

The modes are then identified by analyzing the estimated acceleration based on the following set of rules developed in accordance with (4.16*)*.

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

For a healthy SI engine the switching between subsystems occurs sequentially and is a deterministic process. Any deviation of mode sequence from that of expected 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 follows: (see Figure-6.2). Also note that for the given application example of SI engine, the correct ignition sequence is assumed to be 1234 for the simulation results.

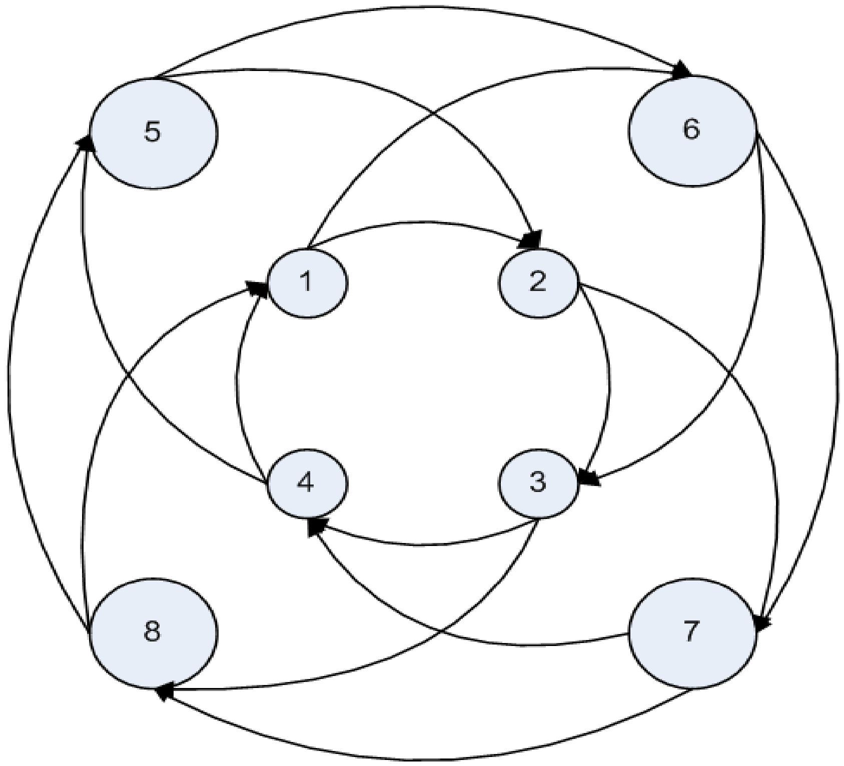

Figure-6.2 SI engine modes with switching sequence

$$\text{Fault free case} \quad \left.\begin{array}{ll} \mu_k \rightarrow \mu_{k+1} & \text{for } k < 4 \\ \mu_k \rightarrow \mu_1 & \text{for } k = 4 \\ \mu_k \rightarrow \mu_{k-3} & \text{for } 8 > k > 4 \\ \mu_k \rightarrow \mu_1 & \text{for } k = 8 \end{array}\right\}. \tag{6.15}$$

$$\text{Faulty case} \quad \left.\begin{array}{ll} \mu_k \rightarrow \mu_{k+5} & \text{for } k < 4 \\ \mu_k \rightarrow \mu_5 & \text{for } k = 4 \\ \mu_k \rightarrow \mu_{k+1} & \text{for } 8 > k > 4 \\ \mu_k \rightarrow \mu_5 & \text{for } k = 8 \end{array}\right\}. \tag{6.16}$$

which implies that

$$\begin{array}{l}\mu_k \in \mu_H \\ \text{or} \qquad . \\ \mu_k \in \mu_F\end{array} \tag{6.17}$$

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

Figure-6.3 describes the complete fault diagnosis methodology.

6.4 Simulation results

This Section gives the simulation results used to validate the above FDI scheme. This is performed by simulating the hybrid model of the SI engine given in Section 6.2, firstly for healthy case and then the process is repeated by introducing the misfire fault in it. The model is parameterized as in [94]. The modes are identified by analyzing the continuous state estimates and the fault is detected by monitoring the identified modes.

For the simulation purposes, the engine model is simulated and data of the active cylinder identification and crankshaft speed is saved in an array. The cylinder identification is assigned when a pulse input is provided to the subsystem. Cylinder ID is assigned a value 1 for first subsystem, value 2 for second subsystem and so on. However, in all the figures given in this Section the Cylinder ID is plotted after suitable scaling for better visualization. The crankshaft speed is obtained from the engine hybrid model and is tracked by the observer for the estimation of crankshaft acceleration. Figure 6.4 shows the crankshaft speed of healthy engine used as the input to the SMO and Figure-6.5 gives the speed profile of the faulty engine used for tracking.

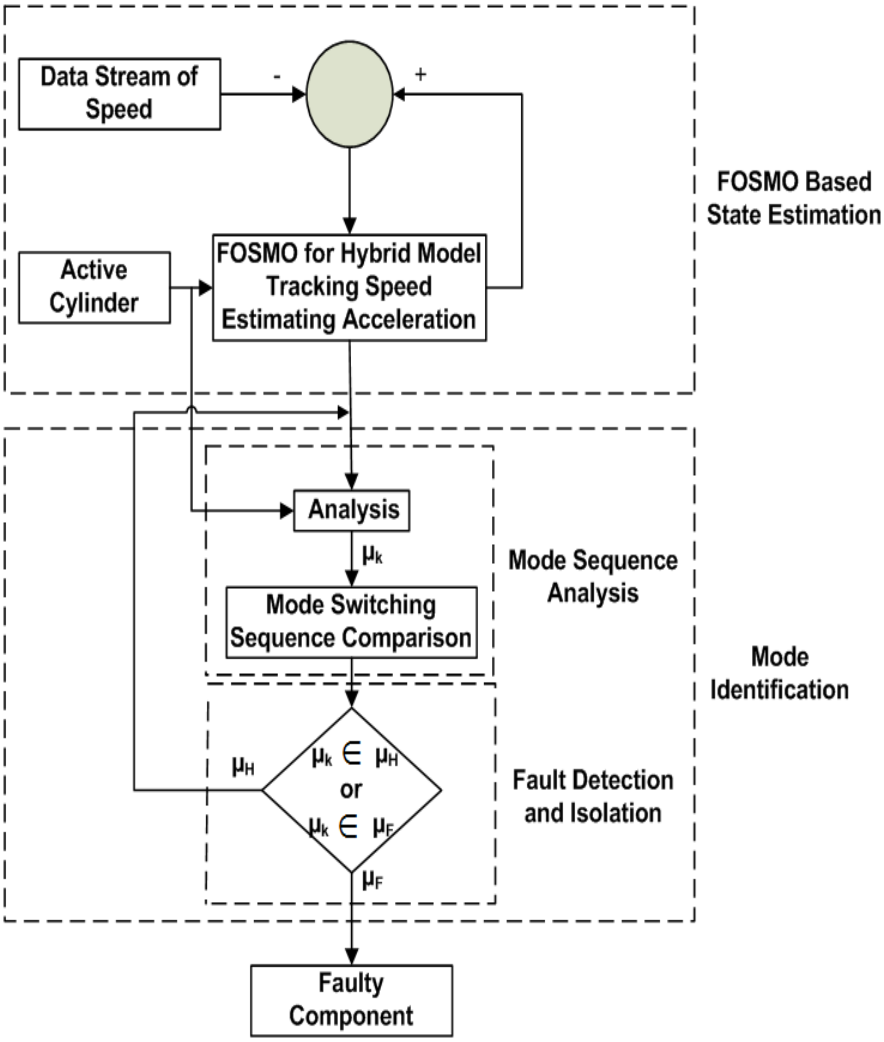

Figure-6.3 Proposed methodology for SI misfire detection and isolation

Figure-6.6 shows the observer tracking for the healthy engine case and Figure-6.7 gives the same result for faulty case. It is evident from these figures that the SMO is tracking quite well. However, as in the case of FOSM, the unwanted chattering effect can be seen in Figure-6.8 that presents the zoomed view of peak of observer tracking response to highlight this. In the present work, we will carry on with the FOSMO for simplicity. Figure-6.9 gives the plot of error obtained in observer tracking and Figure-6.10 shows the estimated acceleration for the healthy engine while Figure-6.11 presents the acceleration estimate for the faulty engine.

Using the estimated acceleration, the modes are identified for the FDI purpose according to the set of rules mentioned in Section 6.3.1. This information along with (6.15) and (6.16) is utilized in the monitoring of the mode switching sequence. So from Figure 6.10, we can clearly find that for healthy engine the analysis of mode switching sequence implies $\mu_k \in \mu_H$. Similarly for the misfire fault in cylinder 1 shown in Figure 6.11, the mode switching sequence becomes as:

$2 \rightarrow 3 \rightarrow 4 \rightarrow 5 \rightarrow 2 \rightarrow 3 \rightarrow 4 \rightarrow 5$

Instead of

$2 \rightarrow 3 \rightarrow 4 \rightarrow 1 \rightarrow 2 \rightarrow 3 \rightarrow 4 \rightarrow 1$

That is, for the misfire case at-least one mode that belongs to the μ_F appears in the mode switching sequence. The presence of mode 5 in the sequence gives the indication that the cylinder 1 of the SI engine is faulty. Appearance of more than one member of the μ_F within one ignition cycle indicates multiple misfires. The simulation results described the use and effectiveness of the proposed scheme for the misfire fault detection and isolation in SI engine.

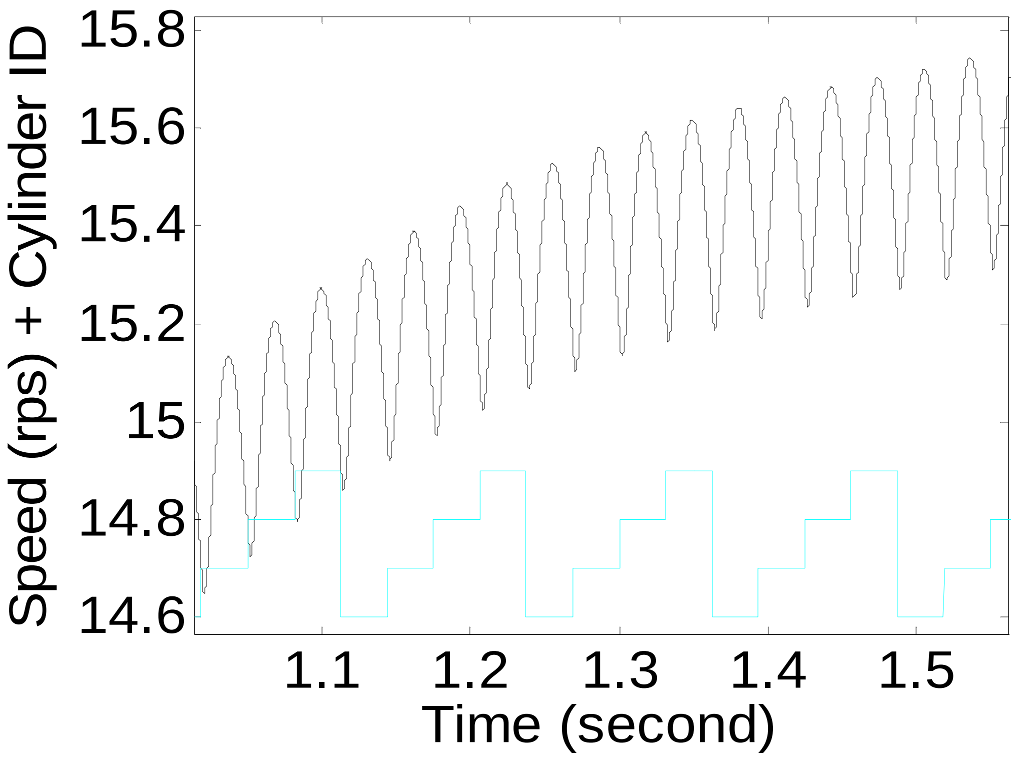

Figure-6.4 Crankshaft speed for fault-free case

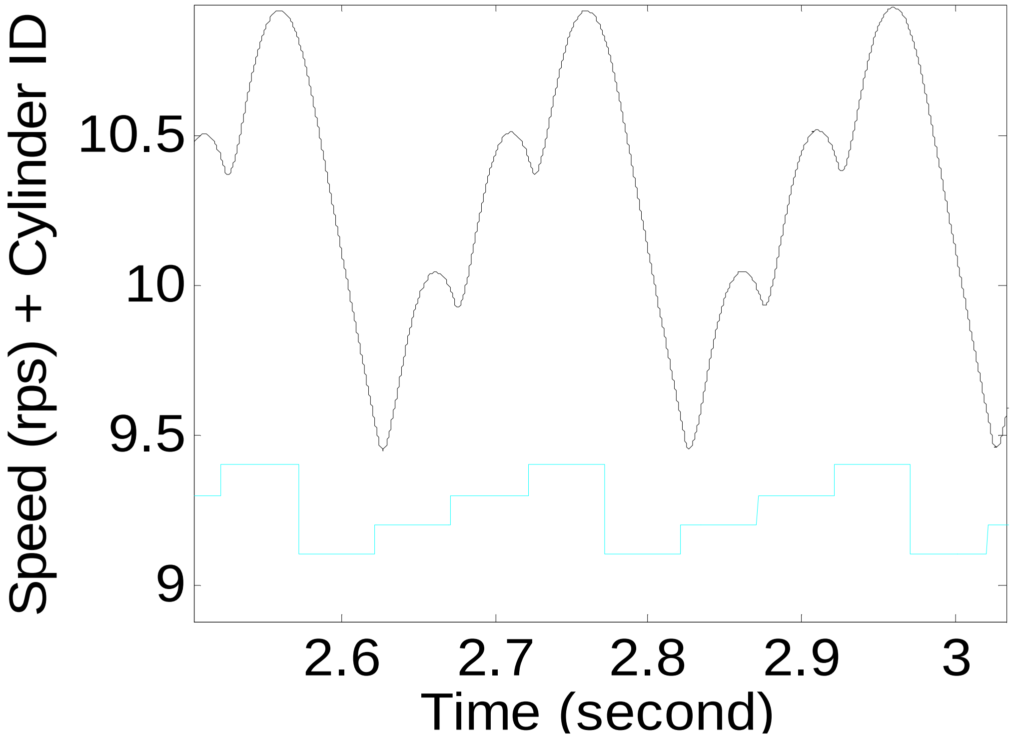

Figure-6.5 Crankshaft speed for misfire fault in cylinder 1

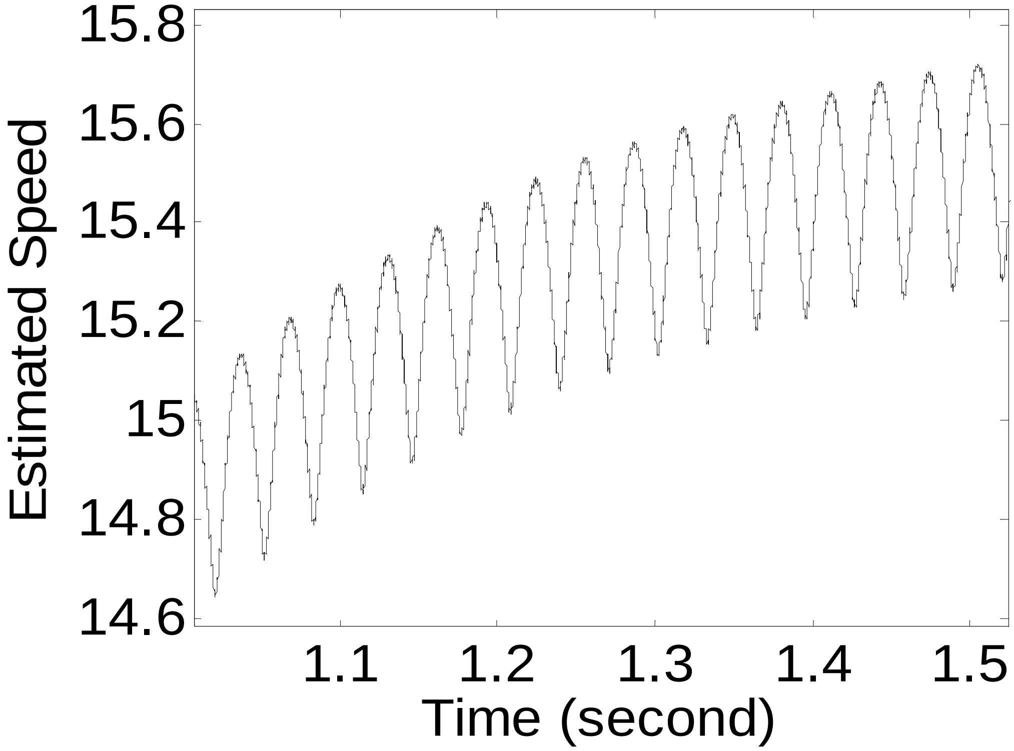

Figure-6.6 Observer tracking for fault-free case

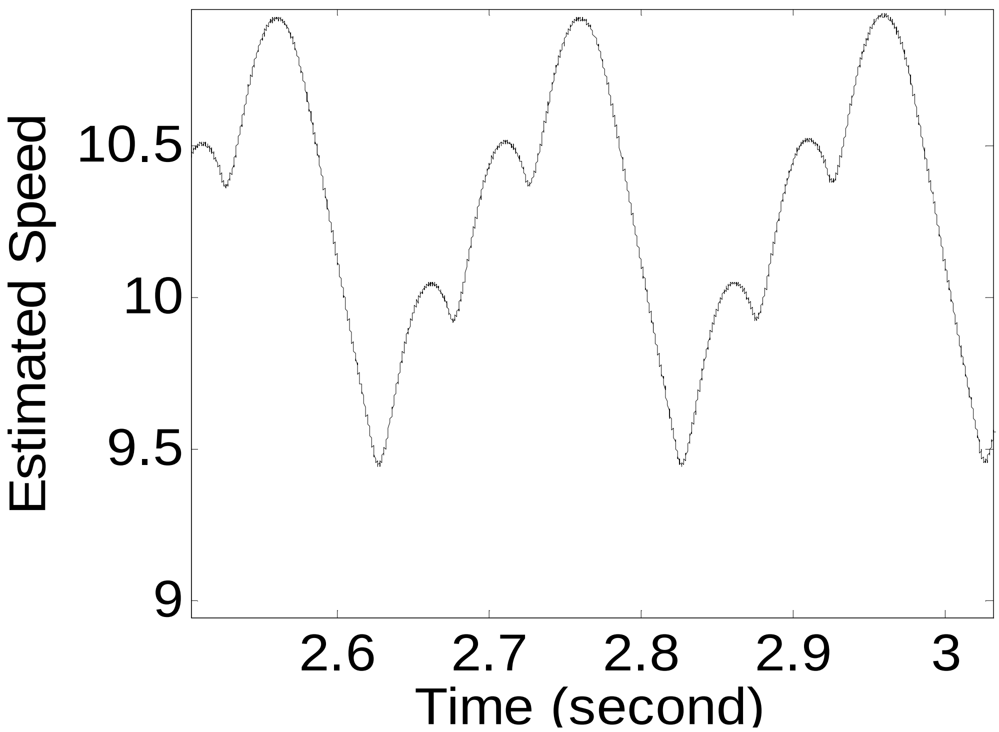

Figure-6.7 Observer tracking for faulty case

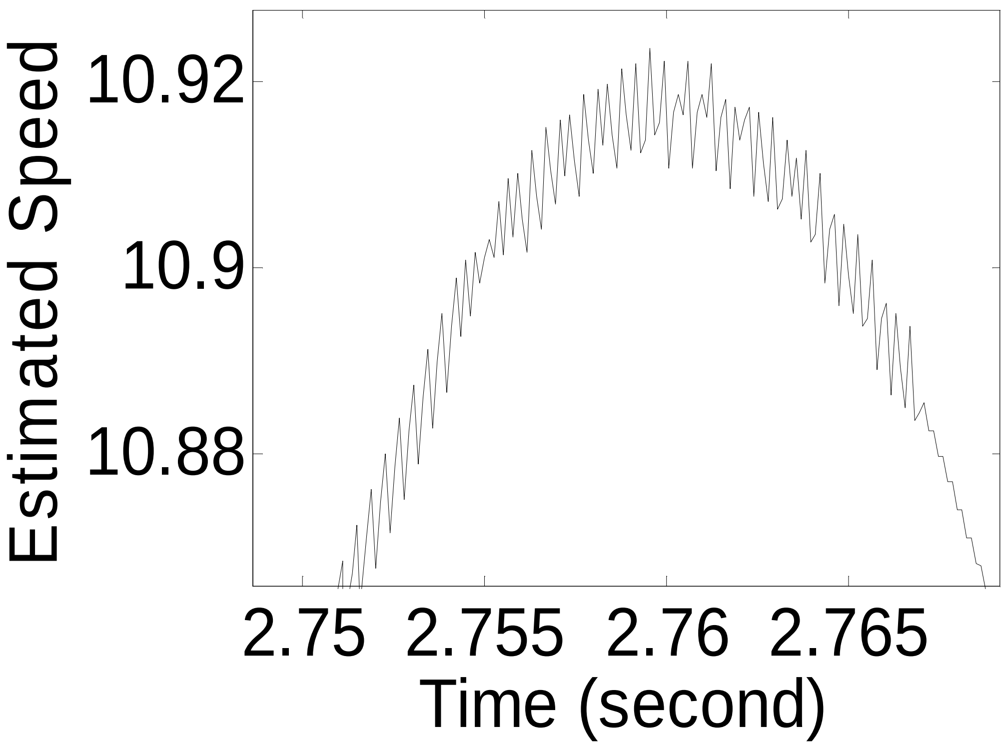

Figure-6.8 Zoomed view of peak of observer tracking

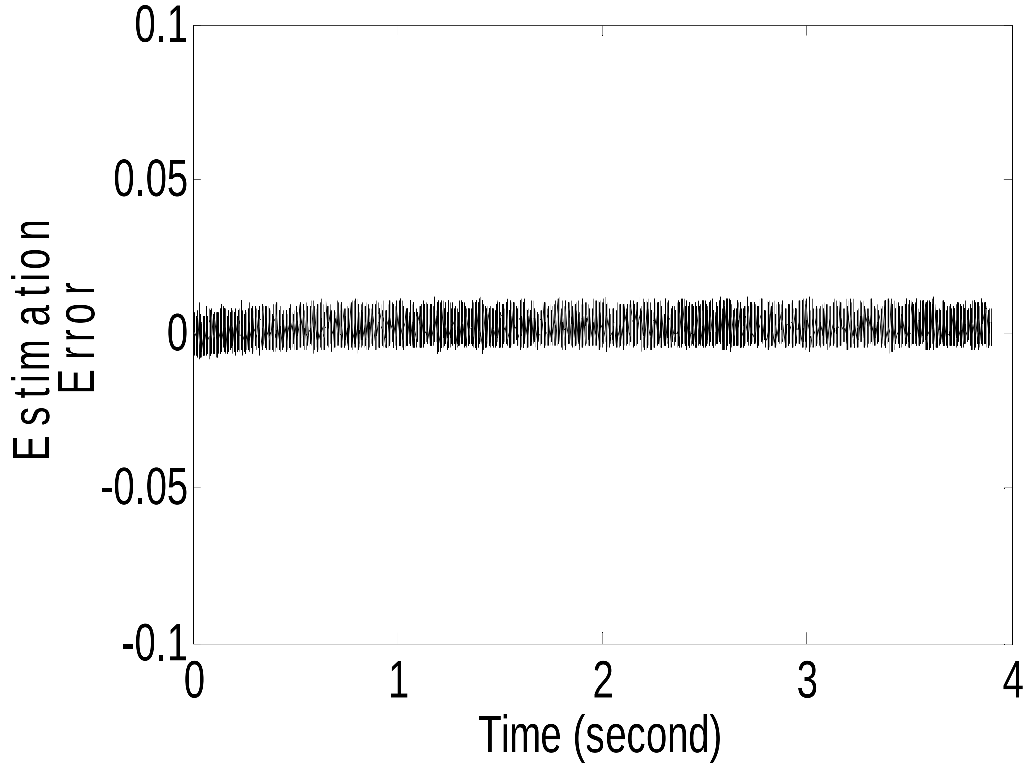

Figure-6.9 Estimation error in observer tracking

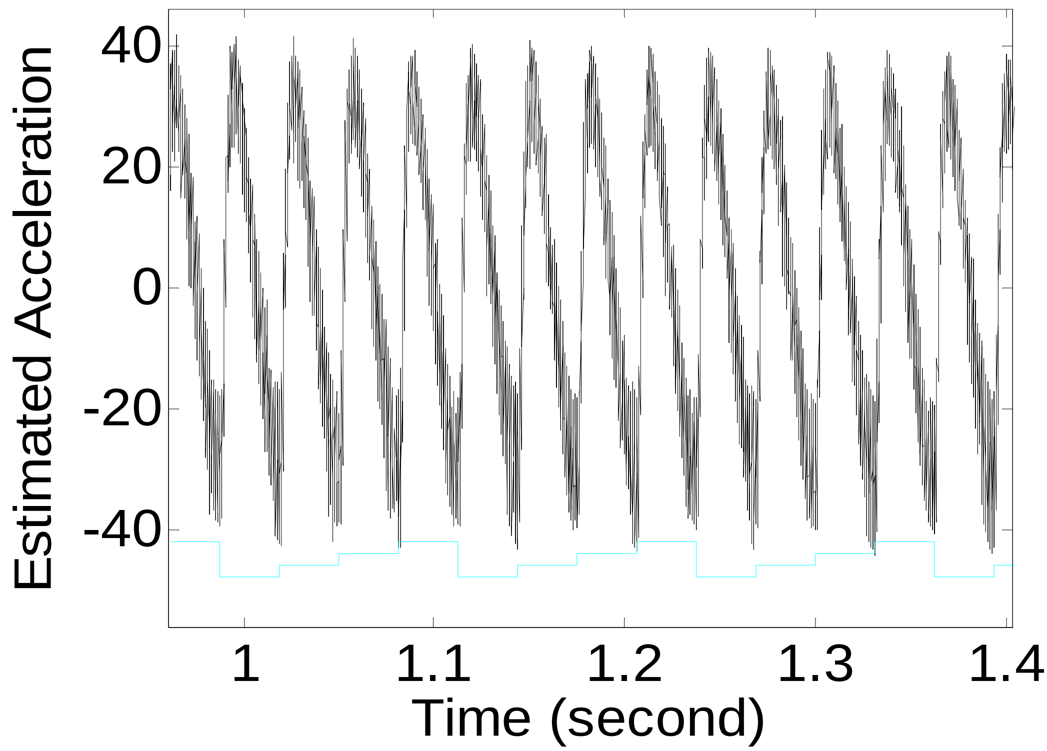

Figure-6.10 Estimated crankshaft acceleration for fault-free case

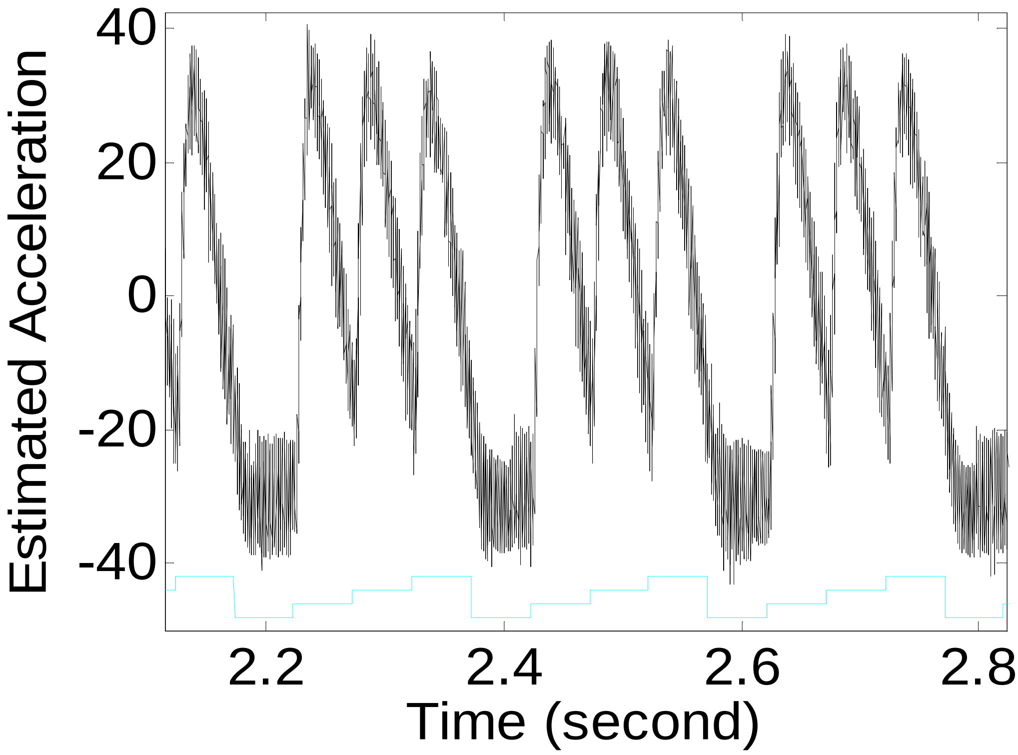

Figure-6.11 Estimated crankshaft acceleration for misfire fault in the first cylinder

6.5 Experimental results

This Section gives the description of the experimental results used to validate the proposed FDI scheme. The experimental set up used for the work presented in this dissertation has already been explained in Section 5.3.4. Data for the validation of the proposed scheme is acquired from an engine rig of 1.3L production vehicle compliant with the On-Board Diagnostic II (OBD-II).

A crankshaft position sensor is always installed in front of a gear assembly in all the EFI vehicles. A missing or double tooth is provided in the gear to act a reference position and to keep track of the cylinder identification. In our experimental rig, the gear mounted for the crankshaft position monitoring contains 13 teeth. So even for very high data acquisition rate, only 13 data points can be acquired for each complete rotation of crankshaft. This low resolution data resulted in noisy signal as compared to the data used in simulations. This noisy data was supplied to the proposed algorithm to ascertain its ruggedness for the practical noisy signals.

For the validation of the proposed FDI scheme, the crankshaft acceleration is required but as mentioned earlier the acceleration sensor is not available in the production vehicle. So we use the FOSMO for the estimation of the crankshaft acceleration by using the crankshaft speed. Data from the crankshaft position sensor is acquired using data acquisition card from the National Instrument Inc. This data was processed to obtain the crankshaft speed signal that is applied to the observer after appropriate filtering.

In the next stage, misfire fault is introduced in the 3rd cylinder of the SI engine by inhibiting the igniter signal to the engine. The same process is repeated again and the speed data is acquired for the misfire case. Figure-6.12 shows the filtered signals of the speed obtained from the experimental measurements for the fault-free case and Figure-6.13 presents the speed signal with the misfire fault in the third cylinder. Figure-6.14 gives the observer tracking error.

For the healthy engine, the estimated acceleration is given in Figure-6.15 and for the misfire case the estimated acceleration is plotted in Figure-6.16. The basic trend of the experimental results shown in Figure-6.15 and Figure-6.16 are sufficiently similar to the simulation results of the estimated crankshaft acceleration shown in Figure-6.10 and Figure-6.11. So adapting the same analysis procedure as in Section 6.4, we validate the proposed scheme experimentally. In case of the misfire fault, the absence of positive peak can be seen in Figure-6.16. The analysis of this data indicates the presence of one mode from the μ_F, thus detecting and identifying the faulty mode.

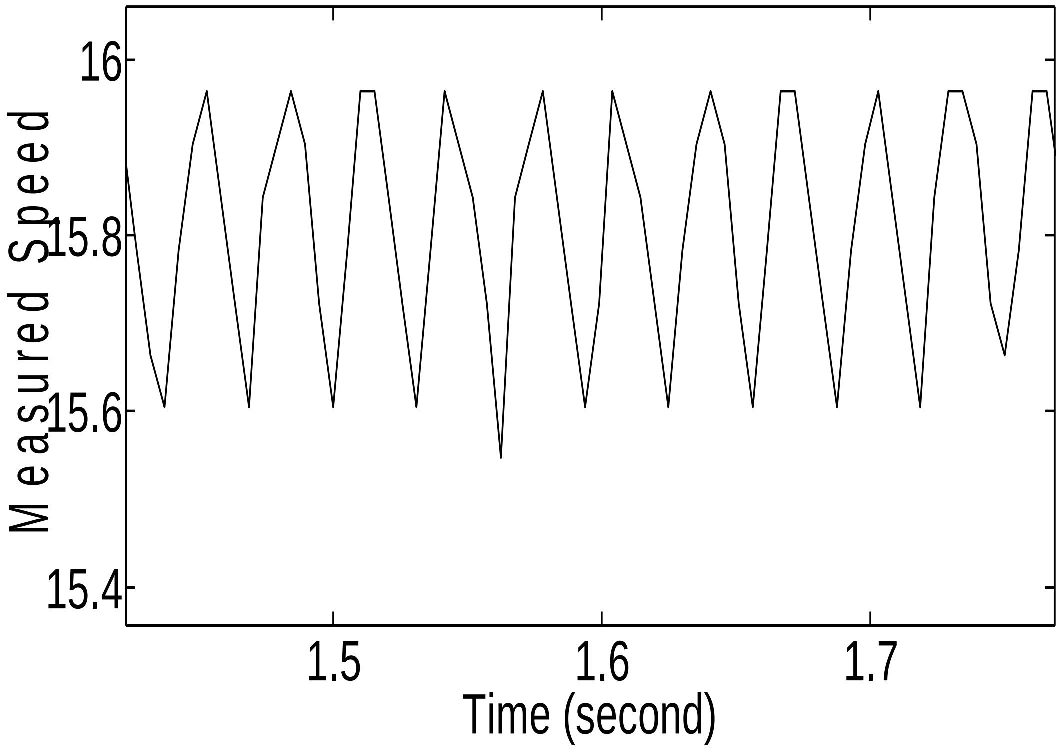

Figure-6.12 Crankshaft speed measurement for fault-free case

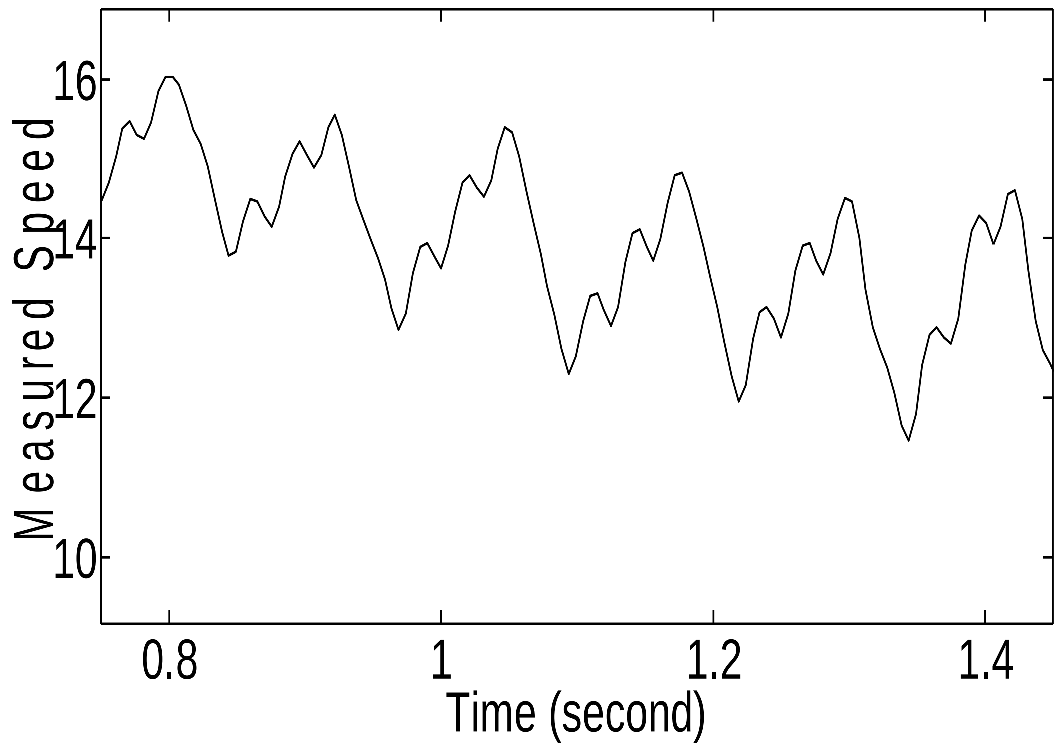

Figure-6.13 Crankshaft speed measurement for misfire fault in cylinder 3

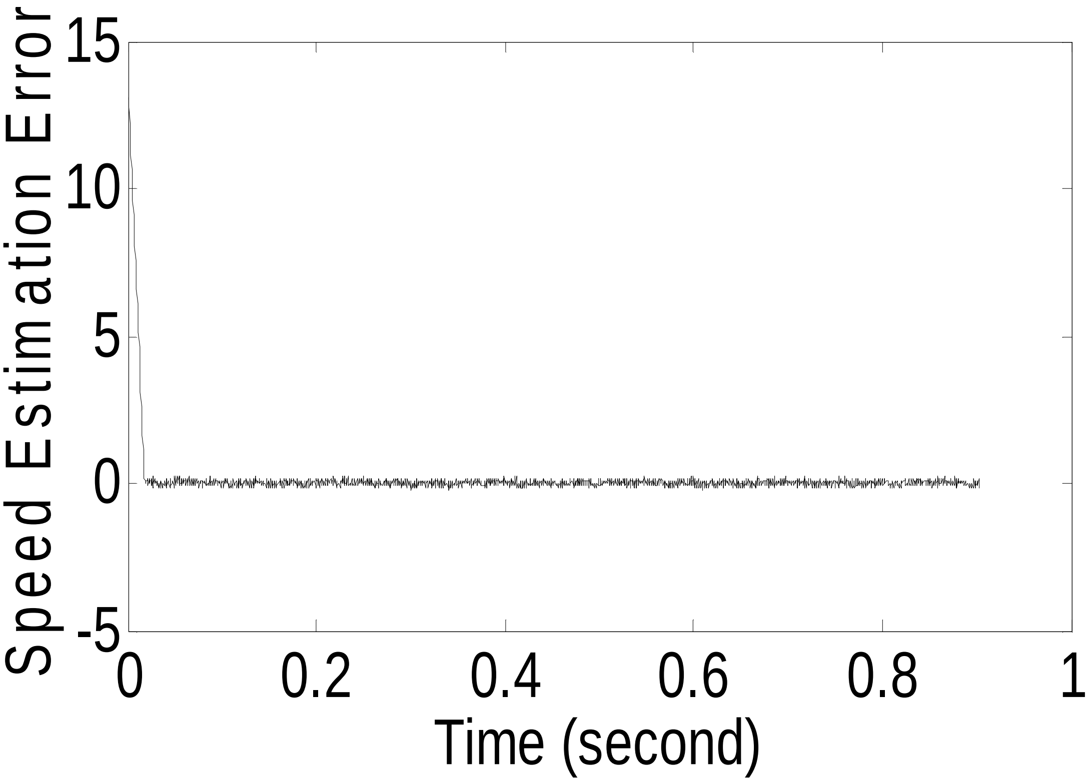

Figure-6.14 Observer tracking error

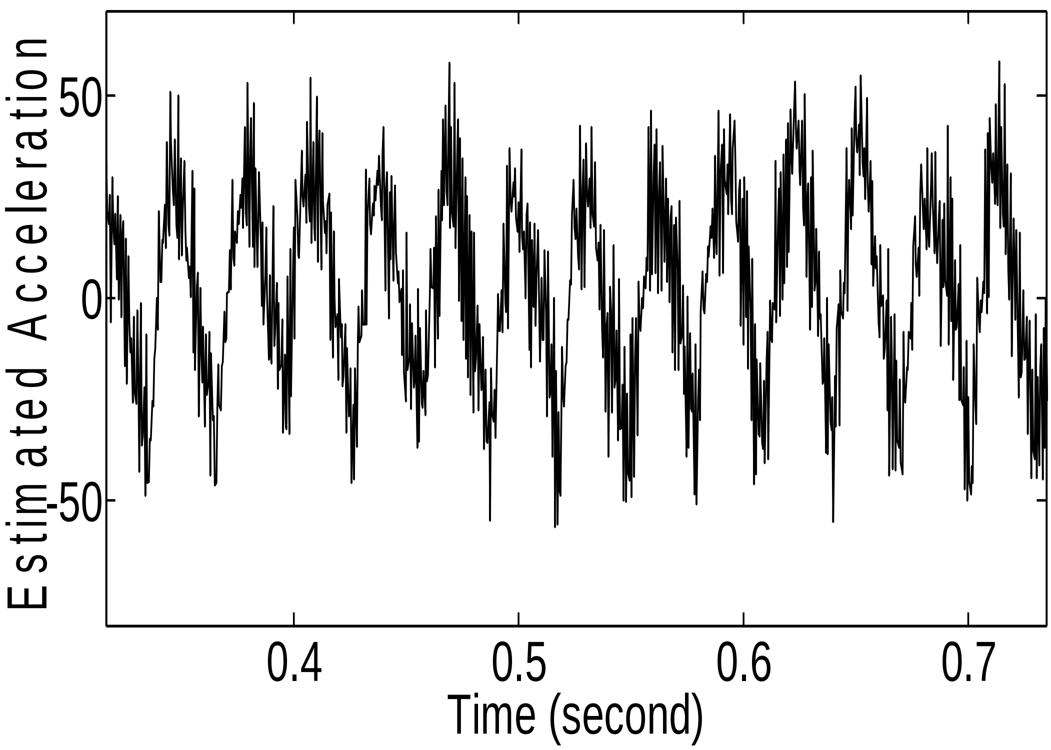

Figure-6.15 Estimated crankshaft acceleration for fault-free case

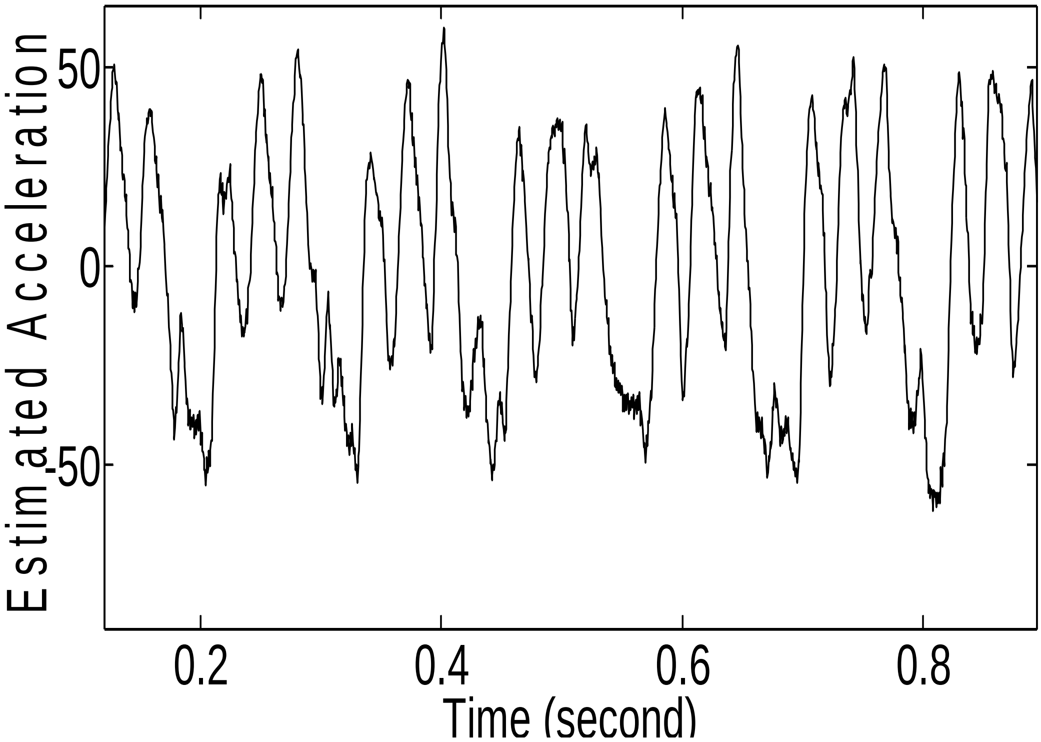

Figure-6.16 Estimated crankshaft acceleration for misfire fault in cylinder 3

Representation of a highly nonlinear SI engine using a switched linear hybrid model provides quite simpler state estimations technique using the SMO. The model also provides an easy way for the association of the modes with the complex non-linear system and the proposed technique demonstrates the application how the mode identification and the allowable mode sequence can be used for the fault diagnosis applications.

6.6 Comparison of methods

This Section gives a brief comparison of the proposed misfire detection technique with some of the others misfire detection techniques available in the literature. In [105], the author worked on both the model-based techniques and the data-based techniques for the misfire detection and accredited that the model-based technique is better on the basis of the error rate. He concluded using his analysis based on the same data set that data-based technique resulted in 18% error rate while in comparison the model-based approach have 8% error rate. The model used in [105] was a nonlinear model involving many computations in each iteration, thus making it computationally heavier. However the procedure has the advantage of the physical reasoning.

Our proposed scheme uses the linear models for the state estimation and is simpler and easier to analyze than the technique adopted in [105]. Moreover, as our proposed scheme is model-based so it shares the advantage of the physical reasoning with [105] method.

In [104], the authors adopted the model-based approach for the misfire detection in the SI engine and used the FOSMO to estimate the unknown cylinder pressure that is further utilized in the misfire fault detection process. The authors acknowledged that the use of the nonlinear sliding mode observer based on the speed measurements provides the cheap, accurate and reliable solution to estimate the desired states. However, the model used in [104] was a nonlinear model in which observability is lost at the TDC.

As we used SMO based on the speed measurement for the state estimation process, so our proposed method shares the simplicity and the reliability of the method given in [104]. Moreover our proposed scheme is simpler as it uses linear models instead of nonlinear one.

In [101], Kalman filters are used for the estimation of acceleration using linear models. However Kalman filters are computationally heavier than SMO and also require the noise matrices Q and R which are difficult to estimate.

Data-based approaches lack the physical insight of the problem while our proposed approach has the advantage of being supported by the physical reasoning. Moreover, most of the data-based techniques are sensitive to factors like engine speed [105]. This can be seen if the correlation analysis is used for the comparison of some recorded signal of faulty engine speed, then for reliable results engine must be operated at the same speed at which the fault signatures were taken. The identification of misfire fault in more than one cylinder, multiple signatures are required to be compared with the observed data. This kind of methodology is adopted in [106] for identification of misfiring cylinder. When the operating speed of engine was not the same at which fault signatures were captured then two signals will have different frequencies and will be difficult to compare. This can be taken care of if large number of fault signatures is taken at various speeds, but this approach will increase the computational requirements.

6.7 Summary

In this chapter, a mode identification scheme is presented for the misfire fault diagnosis in SI engine. Modes are defined in terms of engine health. The modes are identified based on the analysis of the continuous states of the system. These estimated modes are monitored to detect and isolate the misfiring cylinder. For the state estimation, a FOSMO is designed based on the hybrid model of SI engine. This observer provided the robust state estimates even in the uncertain and noisy environment. The proposed technique, being model-based, has the advantages of physical reasoning, simplicity and easy implementation.

The validation of the proposed scheme is performed through simulations and experimental data and the results obtained are presented with discussion. An engine rig of 1.3L production vehicle is used for the acquisition of the experimental data. The proposed technique correctly detected the misfire fault even in the presence of this noisy data, which gives a clear indication of the robustness of the presented misfire detection scheme.

CHAPTER 7

CONCLUSIONS AND FUTURE WORK

This chapter gives a summary of the whole work presented in this dissertation along with some future directions. The presented work is related to the FDI of hybrid systems, in which we focused on a special class of these systems known as SLS. Hybrid systems enable us to represent a complex engineering system in smaller, simpler interacting subsystems. Due to the increased complexity, chances of the fault occurrence in complex engineering systems are also high. Moreover, the design of the FDI schemes for these systems is also becoming complex. This dissertation proposed simple and easy to implement FDI schemes for these complex engineering systems by representing them as a set of simple interacting subsystems. This is achieved by using hybrid models of these complex engineering systems and designing FDI scheme using state estimation and specific methods of hybrid model. Furthermore, instead of using Kalman filter for state estimation in the FDI process, SMO is adopted that is computationally lighter and easy to implement.

For identification and monitoring of hybrid systems, mode identification is a natural way and key step. Two types of fault can be considered in hybrid systems; ones related to the current mode behavior and the others affecting the discrete evolution trajectory. These both types of fault can be detected by defining and identifying healthy and faulty modes, and monitoring their sequence by designing a DFA that takes as inputs the modes of the hybrid systems represented as symbols of a language acceptable to the DFA. New faults can be detected and isolated by introducing new strings and using additional states in the DFA.

The proposed FDI scheme was validated through simulations and experimental data. Data for the experimental validation of the proposed scheme is acquired from an engine rig of 1.3L production vehicle complaint with the OBD-II. This engine is equipped with the ECU complaint to the OBD-II standards. Using the acquired data, system states are estimated by the SMO based on the hybrid model of the SI engine and are analyzed for the mode identification from the FDI perspective. The identified modes are then monitored by the DFA for fault detection and isolation.

After a brief summary of the presented work, the description of the main contributions of this dissertation is given in the next Section.

7.1 Contributions

The main contributions of the thesis are summarized as:

- A mode identification scheme is proposed for the FDI of an important class of the hybrid systems known as the Switched Linear Systems (SLS). The states of the SLS are estimated using SMO stack and are analyzed to identify modes to be used in the FDI process. Detection and isolation of new faults can be easily made by introducing new strings in a set, called as *fault set* in this dissertation.
- A mode identification scheme is proposed for the FDI of SLS having identical subsystems. The presented scheme also covers the SLSs with identical subsystems that were not taken care of by the previous scheme. The proposed scheme is successfully validated through a Spark Ignition (SI) engine having identical subsystems.
- To monitor the identified modes sequence for the FDI a SLS, a Deterministic Finite Automaton (DFA) is designed that provides the benefits of detecting and isolating the fault in SLS at the same time as well as identifying the corresponding dynamics of the SLS involved in the fault occurrence. The identified modes are used at the input of DFA as symbols of a language acceptable to it. In hybrid systems, two types of fault can be considered. The use of proposed DFA in the FDI of hybrid systems makes it possible to diagnose these both types of fault by using a single scheme.
- Development of a mode identification scheme for the detection of the misfire fault in the SI engine. The experimental data is acquired from a four cylinder SI engine of 1.3L production vehicle. Using hybrid model of the SI engine, a hybrid observer is designed and based on the identified discrete event the continuous model of the corresponding subsystem is selected for the design of SMO. The observer output is finally analyzed in the mode identification and fault diagnosis process.

7.2 Future work

The work presented in this dissertation can be extended for the following new directions of research.

- In this dissertation, we used FOSMO for the estimation of states of the hybrid system. FOSM has inherent properties of finite time convergence, simple design and robustness. However it suffers from the unwanted chattering phenomena. This can be tackled by using the High Order Sliding Mode (HOSM) that retains these vital properties of the FOSMO and also minimizes the chattering effect. The existing work can be extended by using the HOSMO for the state estimation of the hybrid systems that can be further analyzed for the FDI purpose.
- It can be explored to develop set of rules for defining the fault set **F** described in this thesis.
- In this manuscript, we analyzed the states of the system for the FDI purpose. We can also exploit critical parameters of hybrid systems for the FDI purpose. However, these parameters, although vital for the FDI, might be un-measureable. In such situations, we need to estimate them first. So this can be divided in two tasks given below.
    - Parameter estimation of the hybrid systems.
    - Development of a parameter estimation based FDI scheme for the hybrid systems.
- SMO can be used to estimate discrete states as well. Similarly HOSMO can also be explored for the estimation of the discrete states.
- Continuous states of the system are estimated for generating the input symbols for the DFA proposed in this work for the FDI purpose. Other techniques, like the one given in chapter 5 that avoid the process of the continuous state estimation, can be explored for symbol generation used by the DFA, thus resulting in the further simplification of the FDI process.
- The proposed approach can be extended for the FDI of discrete faults in the switched systems having identical subsystems.

- The proposed FDI schemes can be explored for the multiple faults case.

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