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PRECEDENT-FREE FAULT LOCALIZATION AND DIAGNOSIS FOR HIGH SPEED TRAIN DRIVE SYSTEMS

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Asad Ul Haq, Dragan Đurđanović

The University of Texas at Austin, Austin, USA

Abstract. *In this paper, a framework for localization of sources of unprecedented faults in the drive train system of high speed trains is presented. The framework utilizes distributed anomaly detection, with anomaly detectors based on the recently introduced Growing Structure Multiple Model Systems (GSMMS) models. Physics based models of the drive system and its pertinent subsystems were derived and were calibrated using data collected over several actual trips on a high speed train. Simulation results demonstrate the ability to localize faults within various parts of the drive train system without the need for models of the underlying faults. In addition, traditional model based diagnosis was utilized for positive identification of faults, with signals emitted by the systems in the presence of those faults being available for modeling and subsequent recognition of faulty behavior.*

Key Words: *Immunity Inspired Diagnostics, High Speed Trains, Growing Structure Multiple Model Systems*

1. INTRODUCTION

A growing concern with the environmental impact of air traffic has contributed to the success and growth of high speed rail as a more sustainable transport medium. Consequently, in recent years the European and Japanese markets have seen a significant transition of traffic from airplanes to high speed rail, especially for journeys up to a few hundred miles long [1]. Studies have also been carried out that underline the benefits of high speed rail as a transport system [2].

The growing popularity of high speed rail has inevitably led to investment in the development of the resources required to ensure reliability of the train systems [3], which is critical to the ability of high speed rail to compete with alternative modes of transport. As such, there is a need to develop systems for condition monitoring that would enable

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Corresponding author: Dragan Đurđanović
The University of Texas at Austin, Austin, TX 78712,
USA E-mail: dragand@me.utexas.edu

detection of faults and localization of their root causes within the system[1]. The increasing complexity of trains running at higher speeds has led to greater challenges in the tasks of detecting faults that cascade through the system, and finding their sources. The first and foremost factor driving the need for such reliable and efficient monitoring systems derives from the safety requirements for high speed trains. In addition to this, there is a two-fold financial significance. First, ensuring reliability is critical as it prevents delays, which becomes a factor in retaining passengers. Second, accurate fault localization contributes to the reduction of wastage of resources on ineffective maintenance.

Unfortunately, monitoring systems based on the classical framework are restricted in their diagnostic abilities, due to their reliance on fault models for these tasks. Namely, the classical diagnostic paradigm requires models of the relevant faults in order to detect their occurrence. Furthermore, these models need to be adequate throughout the operating space which the system experiences. Therefore, a monitoring system under the classical framework is unable to deal with faults that have not been foreseen or for systems in operating regimes for which diagnostic models were not trained. This is of particular significance for highly complex system operating under highly variable operating regimes, such as the drive train of a high speed train. For such systems, it becomes unfeasible to build models of all possible faults, under all operating conditions. This strongly implies the need for a precedent-free fault detection and isolation approach.

In this paper, the method for precedent-free fault detection and localization introduced in [4], and further developed in [5], is employed to facilitate monitoring of high speed train drive systems. The methodology presented in [4] spans the tasks of fault detection, localization and identification in complex systems of interacting dynamic subsystems. Anomalous behavior of the system is detected as a statistically significant departure of its behavior from the normal one. The detection of a fault triggers the distribution of anomaly detectors (ADs) across the subsystems of the faulty system, spreading into increasingly granular levels of subsystems that exhibit deviation from their own models of normal behavior. This process of AD proliferation continues as each AD that detects a fault is replaced by multiple ADs monitoring the constituent subsystems of the faulty system. Thus, the source(s) of the fault(s) is (are) localized, as part(s) of the system surrounded by alarming ADs, in a hierarchical manner once the highest possible level of granularity of subsystems is reached. This distributed anomaly detection based on an a priori known structure of the monitored system[2] has been shown to enable precedent-free fault root cause localization [6]. The entire process is based solely on models of normal behavior, thereby bypassing the need for fault models, which, as previously mentioned, is a major constraining factor in the applicability of traditional diagnostic methods.

After faulty subsystem(s) is (are) located, the natural next step is fault diagnosis, which involves identification of corresponding fault models so that such behavior may be recognized in the future, and possibly remedied via fault-tolerant controller adaptation or maintenance intervention. This obviously amounts to the traditional diagnostic paradigm of recognizing known faults based on their models, or building new fault models when the currently observed behavior of the monitored system does not match any existing fault model. Such fault models can be built based on knowledge about system physics, as well as historical experience and observations of system operation.

[1] Reliably and efficiently determining which part of the system is at fault
[2] Knowing what subsystems constitute it and what their respective inputs and outputs are

The novel diagnostic framework briefly described above has previously been successfully implemented for fault detection, localization and diagnosis in the electronic throttle and crankshaft systems of an automotive internal combustion (IC) engine [4] [7], Exhaust Gas Recirculation System of an automotive diesel engine [5] and most recently, distributed thermo-fluidic systems [8]. In this paper, this approach is employed for monitoring the drive system of a high speed train. A drive system in a high speed train is a complex system which incorporates linear and non-linear subsystems with continuous as well as discrete inputs and outputs. These factors contribute to a tremendously increased complexity for the monitoring task at hand[3].

The remainder of this paper is organized as follows. Section 2 describes the Growing Structure Multiple Model Systems (GSMMS) modeling approach, which is used as the foundation of the ADs in this work. It also describes the GSMMS-based anomaly detection and isolation procedures. Section 3 describes the physics based and data driven modeling of the system and Section 4 goes on to describe the implementation of the framework to the system in question and the results thereof. Finally, the conclusions and suggested future work are presented in Section 5.

2. DIAGNOSTIC FRAMEWORK

The diagnostic framework described in the previous section does not require fault models for localization of the sources of abnormal behavior of the monitored system. Instead, it only requires models of normal behavior for all the relevant subsystems, which form the basis of the ADs distributed across the system. The recently introduced GSMMS approach for modeling nonlinear dynamic systems [4] is exploited to create the aforementioned models and this section will briefly look into the motivation for the use of this modeling paradigm, as well as summarize methodological traits of the GSMMS model. Further, this section will also discuss how the distributed anomaly detection framework can be used to facilitate precedent-free localization of culprit subsystems causing anomalous behavior of the monitored system.

2.1 Modeling of dynamic behavior

Traditional anomaly detection methods, based on global models of system behavior, focus on characterizing probability distributions of behavioral features and detecting anomalies as changes in those distributions. For systems that do not involve interactions between various constituent subsystems, such anomaly detection approaches are appropriate. However, interactions with other subsystems mean that shifts in the dynamic behavior of a constituent subsystem may not occur solely due to changes in the system dynamics (i.e. real faults), but also due to changes in the operating regime (which should not be seen as anomalies). Namely, changes in the upstream subsystems, whose behavior affects the monitored system, cause shifts in the operating regime of the monitored system, potentially leading to changes in the behavior of the modeling residuals of the relevant anomaly detector and, consequently, false alarms.

[3] Requiring the use of more distributed ADs and a higher level AD hierarchy than the cases reported in the literature on precedent-free diagnostics so far

Such a situation necessitates the use of modeling and anomaly detection approaches that have the potential to separate abnormalities caused by unusual operating conditions (which are not truly anomalies) and true anomalies due to changes in the internal dynamics of the monitored system. To that end, one can utilize "divide and conquer" approaches, pursued in e.g. [4, 5, 7, 9, 10], where the operating space of the monitored system is indexed using features from other systems affecting it. Divide and conquer models decompose the operating space into regimes of similar dynamic behavior, permitting the diagnostic framework to deal with regime-switching induced behavioral shifts. By postulating relatively tractable models in each operating regime, a set of region-specific anomaly detectors can be utilized. The behavior can then be considered independently in each operating regime and the presence of a fault can be detected as unusual behavior of modeling residuals within any of those operating regimes (i.e. corresponding to any of the local models within the divide and conquer modeling framework).

Within the GSMMS framework, the regionalization of operating regimes of a system is conducted via unsupervised clustering of its inputs[4] and initial conditions using a Kohonen Self-Organizing Map (SOM) [11]. The use of such an unsupervised approach for partitioning the operating space overcomes the drawbacks associated with *ad-hoc* or *variable-by-variable* approaches [12-14]. In addition, growing mechanisms, such as those reported in [15-17], enable the determination of the number of local models required to approximate the underlying nonlinear dynamics, with a desired accuracy.

The Growing Structure Multiple Model System can be seen as a collection of local models, with a local model capturing the dynamic behavior in each operating regime. The simple and tractable linear ARX type models were used for the work presented in this paper, allowing easy parameter estimation and interpretation of local models. Essentially such a GSMMS formulation casts the problem of representing the system dynamics into the framework of interconnected, analytically tractable linear dynamic models. Even more simply stated, it approximates a curved surface (non-linear) with a set of appropriately shaped and sized flat tiles (linear models), where the number, shape, size and location of the tiles is determined via a growing SOM. This structure enables the modeling of complex systems, such as the drive system of a high speed train, while maintaining analytical tractability and an operating regime decomposition that enables regionalized anomaly detection. The GSMMS approach has been used successfully for modeling an electronic throttle system in a gasoline engine [9], automotive crankshaft dynamics [7], diesel engine Exhaust Gas Recirculation (EGR) system and its subsystems [5], electrical portion of an alternating current generator [10] and a distributed thermo-fluidic system [8].

Further details, including the mathematical details and graphical representations, of this modeling approach can be found in [18].

2.2 Method for detection, isolation and diagnosis of an anomaly

Anomalous behavior can be seen as a statistically significant departure of the current dynamics of the target subsystem away from the normal one. Once a GSMMS model of normal behavior is built for each system to be monitored, anomaly detection can be

[4] These inputs are often outputs of other systems affecting the behavior of the monitored system.

accomplished through comparison of the statistical characteristics of its residuals[5] displayed during normal behavior with characteristics of the most recent modeling residuals. Since the operating space is decomposed into regions within which a linear model describes the system dynamics, each GSMMS region can be equipped with its own decision making scheme that quantifies how close the current residual pattern is to the normal pattern. Following [9], the performance within each operating region will be described in this paper using the concept of regional confidence values (CVs), defined as the area of overlap of the probability density function (PDF) of the modeling residuals displayed during normal behavior and the PDF of the residuals corresponding to the current behavior, in that region. Based on their universal approximation ability, Gaussian Mixture Models (GMMs) were used to approximate the PDFs [19], which allows efficient recursive updating of the PDFs during operation to obtain the most recent distributions [20], as well as analytical and thus, fast calculation of the distribution overlaps (CVs).

With the above definition, one can see that the CV will be close to 1 when there has been no significant change in the local dynamics of the monitored system, while any notable shift in the local system dynamics will result in lower CVs, with 0 being the lower bound. Following [9] the global CV for the monitored system is then quantified as the geometric mean of the local CVs. This choice of global CV prevents the masking of a fault that is apparent only in certain operating regimes. Namely, a low CV in any given operating regime will force a low global CV for the system, even if the performance is not affected in other operating regimes.

Isolation of the anomaly source can be conducted by proliferating anomaly detectors (ADs) to monitor subsystems of the anomalous system, all of which utilize only models of normal behavior of the system they monitor. Effectively, once an anomaly is detected, the proliferation of the ADs monitoring the pertinent subsystems of that target system is initiated, enabling monitoring and anomaly detection in subsystems of ever finer granularity. Such distributed anomaly detection leads to progressively finer localization of the fault through the hierarchy of the overall monitored system, until the finest feasible granularity is reached[6].

Once the fault is localized to a subsystem, the next step is to recognize the underlying fault (if the model of that fault exists) or recognize that the underlying fault is unknown. A diagnoser for a specific fault can be constructed following essentially the same approach pursued for the purpose of anomaly detection. Signatures emitted in the presence of the fault that the diagnoser needs to recognize can be utilized to estimate the PDFs of the modeling residuals of that diagnoser in the presence of that fault[7] (residuals of the GSMMS corresponding that fault). Proximity of the most recent system behavior to that fault can then be evaluated via the overlap between the PDF characterizing the most recent residuals of the fault model and that corresponding to the residuals of the fault model observed in the presence of the fault it is supposed to recognize. Whenever this

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[5] The modeling residuals are differences between the system output and the output of the GSMMS describing the normal system behavior [28]

[6] The level of granularity is effectively determined by the availability of signals from the monitored system and its subsystems. Generally, the ideal situation is to have access to all relevant inputs and outputs from all Field Replaceable Units (FRUs) in the system, which would enable localization of all anomalies to the level of components that can be directly replaced during maintenance.

[7] These PDFs serve as the equivalent of the PDFs representing normal behavior in the anomaly detection task.

CV-like value for a specific fault model is close to 1, it can be concluded that the corresponding fault is present and a value of this CV-like index close to 0 would imply the absence of that fault. If for none of the existing diagnosers this CV-like overlap happens to be close to 1, the presence of an unknown fault can be inferred and a new fault model must be developed to enable recognition of this fault in the future.

3. MODELING THE HIGH SPEED TRAIN DRIVE SYSTEM

In order to implement the distributed anomaly detection to the drive system of a high speed train, GSMMS models for the system and its pertinent subsystems must be developed. To this end, a physics based model was first built based on a combination of expert advice and available literature. The model was built in Simulink® and simulated using velocity profiles collected from actual TGV train journeys between Paris and Metz, in France. The simulations generated data for the inputs and outputs of each of the subsystems of interest, which was then used to develop the relevant GSMMS based ADs.

The overall system receives a reference velocity as the input, while the actual velocity generated by the drive system is the output. It is composed of a controller, electrical supply, drive motor and mechanical transmission, as illustrated in Figs. 1 and 2. These figures show the major components of the Simulink® model utilized. In addition, it was assumed that sensors were available to collect the input and output data pertaining to each of these subsystems, as well as their component subsystems.

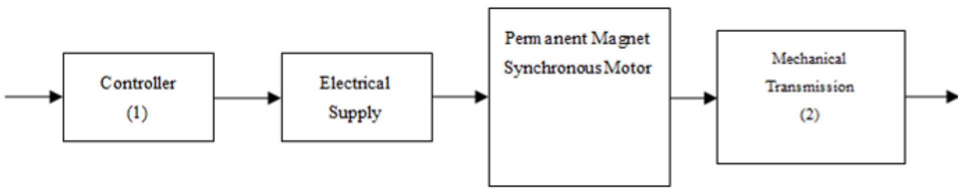

Fig. 1 High speed drive train system

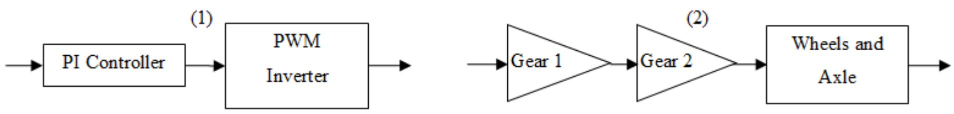

Fig. 2 Components of controller and mechanical transmission systems

The drive motor was taken to be a permanent magnet synchronous motor (PMSM), as per [21]. PMSM modeling has been tackled in the literature in various ways, commonly using a transition of the electrical component from the physical 3-phase structure to an equivalent 2-phase right-angled structure, enabled by the Clark Transformation [22]. In this paper, we used model of PMSM dynamics developed in [23]. Following [24], the controller was taken to be a simple proportional-integral (PI) controller, with a pulse width modulating inverter. Finally, the mechanical transmission subsystem consists of two gears and a wheel and axle combination [21], each of which was modeled simply as a proportional gain. The wheel size required for the gain of the wheel and axle was set as per the information available in [25].

In order to make the data generated as representative of the real world conditions as possible, the reference velocity profiles were collected during actual high speed train journeys in Europe. Four such profiles were collected, one of which was used for training and the other three for testing of the proposed diagnostic approach. These profiles were gathered using a mobile phone based Android application called 'My Tracks' [26], which tracks position, velocity and height using GPS signals. The measurement of interest here is the velocity profile, an example of which is provided in Fig. 3 as a screenshot from the mobile phone.

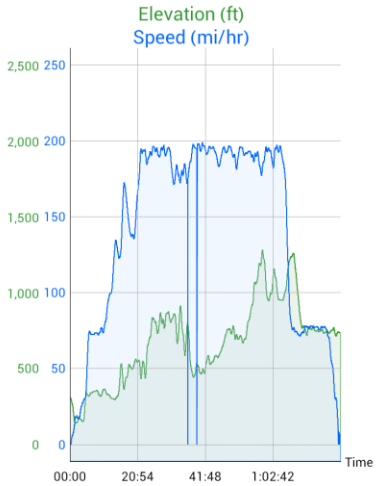

Fig. 3 Example reference velocity trajectory

Once the physics based model was built, data collected from the simulations were used to build the required GSMMS based ADs for all the relevant subsystems of the drive train. The orders of the local ARX models within the GSMMS, were set ad hoc, although techniques for the automated selection of these parameters can be found in [27].

4. Simulation of Distributed Anomaly Detection

With the GSMMS based ADs available to monitor each subsystem, the distributed anomaly detection approach was put to the test. The hierarchy of the AD distribution is shown in Figs. 4 and 5, displaying the AD associated with each monitored system and subsystem. The fault localization process commences at AD_1 which monitors the overall drive train system. Once a fault is detected by AD_1, AD_2 – AD_4 are activated and they begin to monitor the controller, PMSM and mechanical transmission systems respectively. The fault is then localized to one of these subsystems and, depending on which system is faulty, either AD_5 and AD_6 or AD_7, AD_8 and AD_9 are activated. AD_5 monitors the PI controller within the controller; hence it and AD_6 would be activated if the fault had been signaled by AD_2. If the fault had been signaled by AD_4, $AD_7 - AD_9$ would be activated respectively monitoring gear 1, gear 2 and the wheel and axle combination.

The faults considered in this paper were limited to the controller and mechanical transmission systems, and were introduced approximately 8 minutes into the journey.

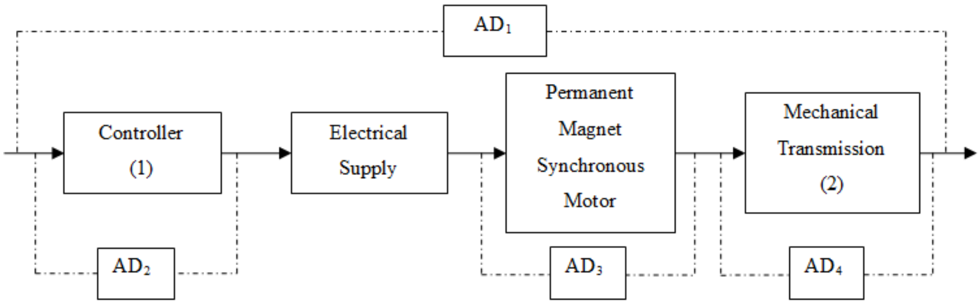

Fig. 2 Levels 1 and 2 of the anomaly detector distribution hierarchy

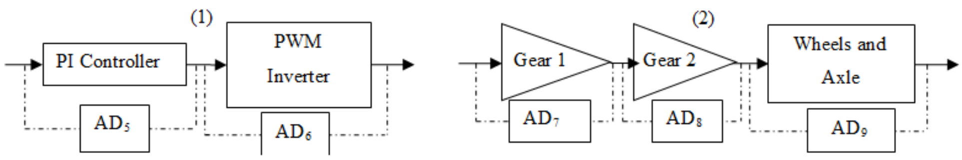

Fig. 3 Level 3 of the anomaly detector distribution hierarchy

4.1 Localization of a fault in the controller

The fault in the controller was introduced in the form of a delay in its output, with delays of 0.7 seconds and 1.4 seconds being inserted in 2 different simulations. The results are presented in the form of the CVs associated with each AD and shown in Figs. 6, 7 and 8. The fault is detected by AD_1 as is highlighted in Fig. 6 by the drop in the associated CV. From Fig. 7 one can see that, of the 3 ADs monitoring the first level of subsystems, only AD_2 exhibits a drop in CV. Hence, the fault can at this stage be localized to the controller subsystem. Finally, it is observed in Fig. 8 that the CV associated with AD_5 drops significantly, while that associated with AD_6 remains high. These results show the fault being tracked through the levels as being local first to the overall system, then the controller subsystem and finally the PI controller.

The approach has hence been able to localize the fault without having any signatures or models associated with the fault in question. In addition, it is noted that no fault was signaled at any of the subsystems that were not faulty, including those interacting with the faulty subsystem. With the anomaly detectors having been set up beforehand, the distributed anomaly detection framework is able to detect the fault online.

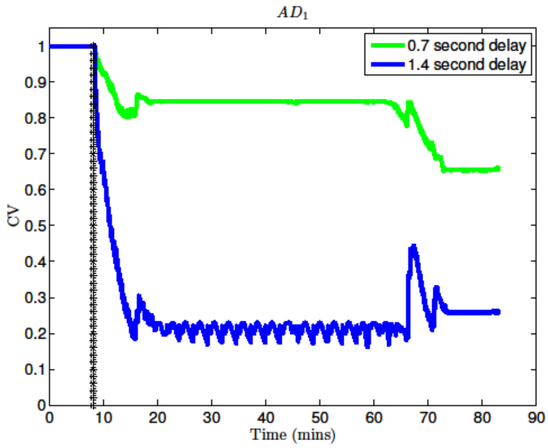

Fig. 6 Controller fault detection response of the AD monitoring the overall system

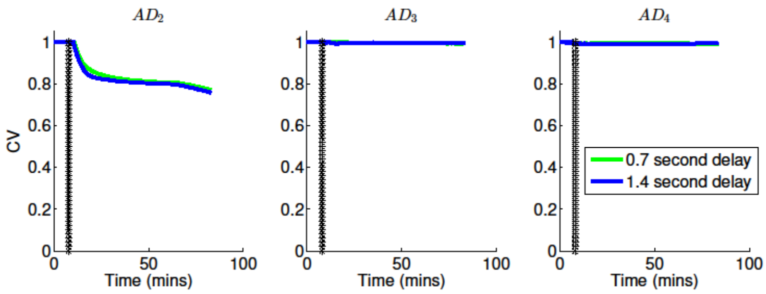

Fig. 7 Controller fault localization at first level of subsystems

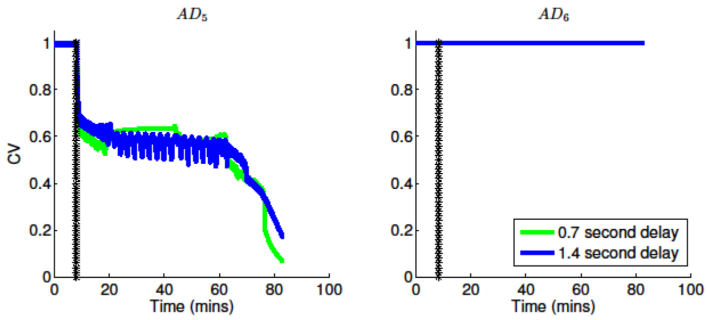

Fig. 8 Fault localization within the controller system

4.2 Localization of a fault in the mechanical transmission

A fault in the mechanical transmission was modeled in the form of added noise to the output from gear 2 to simulate a chattering type fault. Once again, the fault was introduced about 8 minutes into the journey and 2 simulations were conducted with added noise at

6% and 10% of the signal, respectively. The resulting CVs for the relevant ADs are shown in Figs. 9 – 11.

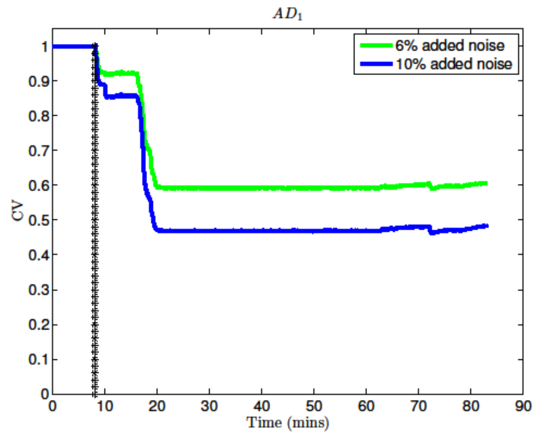

Fig. 9 Gear fault detection response of the AD monitoring the overall system

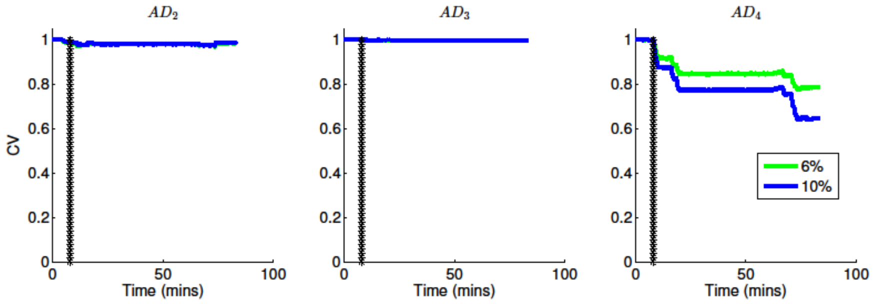

Fig. 10 Gear fault localization at the first level of subsystems

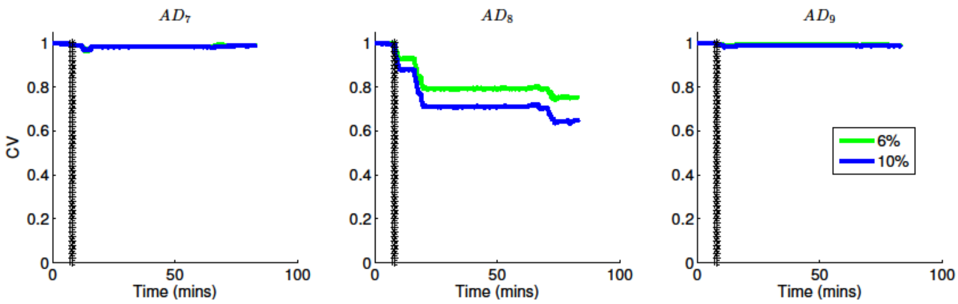

Fig. 11 Gear fault localization within the mechanical transmission system

The CVs shown in Fig. 9 provide clear indication of the presence of a fault in the overall system. Per the proliferation of anomaly detectors described in 2.2, this activates

AD_2 – AD_4 whose CVs are shown in Fig. 10 localize the fault to the mechanical transmission, implicated by the falling CVs in AD_4. The continued proliferation leads to the activation of AD_7 – AD_9, in Fig. 11 the CVs of these ADs isolate gear 2 as the source of the faulty behavior. Whenever the next maintenance opportunity arrives the maintenance team will know exactly which component requires their attention, thereby saving time on inspection and offline fault localization.

4.3 Fault diagnosis

Utilizing the methodology described in Section 2.2., diagnosers were trained for the 2 faults introduced into the gear (6% and 10% added noise to the output). The diagnosers were connected as shown in Fig 12, where Diagnoser 1 (D_1) refers to the diagnoser trained using signals received in the presence of 6% added noise, and Diagnoser 2 (D_2) was trained using the signals gathered in the presence of 10% added noise. The diagnosers were tested by introducing each of the faults that they were trained to recognize at the start of a journey and allowing them to persist for the full duration of that journey. During the first trip, the train was in its in normal operating mode, thereafter the fault corresponding to D_1 was introduced for the next journey and finally the last journey was completed in presence of the fault corresponding to D_2. The results of the diagnosis are presented in Fig. 13, where we can see that, during each stage the CV associated with the appropriate diagnoser (or normal operation monitor) is the highest.

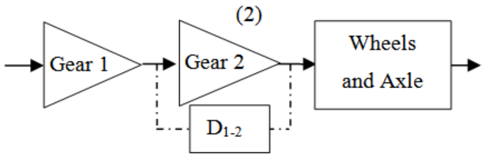

Fig. 12 Configuration of the Diagnosers within the mechanical transmission

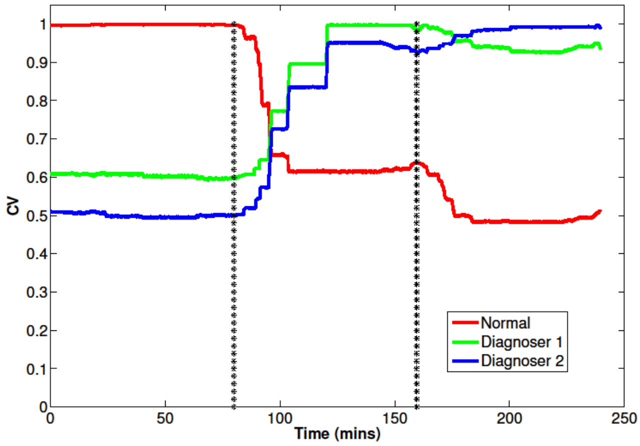

Fig. 13 Diagnosis results for chatter type fault in gear

However, it is also observed that the crossover of CVs is not instantaneous, rather it takes some time for the diagnosers to raise or lower their CVs in response to the change. This is an inevitable result of the recursive updating of the PDFs used to calculate the CVs. Hence, in order for a fault to be diagnosed it must persist for some time. Another important observation is that the fault recognition did not perform well if the subsystem remained in steady state operation. However, given that the train is not expected to continue in steady state operation until the maintenance opportunity, this does not present a major difficulty. Hence, such diagnosers can be used to recognize a fault that has previously been experienced, or for which a fault model is available a priori.

3. CONCLUSIONS AND FUTURE WORK

A recently introduced distributed anomaly detection framework is utilized for precedent-free fault localization in the drive system of a high speed train. The framework uses Growing Structure Multiple Model System (GSMMS) models of the monitored system to describe its dynamics and a statistical measure of departure away from normal behavior for fault detection. GSMMS-based anomaly monitors distributed across the system were then used to localize the sources of anomalous behavior without the need for signatures or models of the underlying faults.

The plant was simulated using a physics based model, which was tuned using data collected from several actual TGV journeys. Simulations of that model were used to generate the data needed to build GSMMS based anomaly detectors for the drive train system and its subsystems. The results of the fault detection and localization accomplished using these ADs show that distributed anomaly detection successfully localizes the faulty subsystems, without any prior information regarding the underlying fault. Further, data generated in the presence of the faults was used to build GSMMS models of the system behavior in the presence of those faults, based on which the faults could subsequently be positively recognized, thus accomplishing fault diagnosis.

The results found here provide several directions for possible future work. A natural extension of the work presented in this paper is the implementation of the precedent-free fault diagnostic approach to hardware-in-the-loop testing environments. Further, the local tractability of the GSMMS modeling approach may be exploited to develop a fault tolerant control scheme for performance recovery. The aforementioned problems are outside the scope of this paper, but are worth pursuing in future research.

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