General Purpose Data-Driven Online System Health Monitoring with Applications to Space Operations

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ABSTRACT

Modern space transportation and ground support system designs are becoming increasingly sophisticated and complex. Determining the health state of these systems using traditional parameter limit checking, or model-based or rule-based methods is becoming more difficult as the number of sensors and component interactions grows. Data-driven monitoring techniques have been developed to address these issues by analyzing system operations data to automatically characterize normal system behavior. System health can be monitored by comparing real-time operating data with these nominal characterizations, providing detection of anomalous data signatures indicative of system faults, failures, or precursors of significant failures. The Inductive Monitoring System (IMS) is a general purpose, data-driven system health monitoring software tool that has been successfully applied to several aerospace applications and is under evaluation for anomaly detection in vehicle and ground equipment for next generation launch systems. After an introduction to IMS application development, we discuss these NASA online monitoring applications, including the integration of IMS with complementary model-based and rule-based methods. Although the examples presented in this paper are from space operations applications, IMS is a general-purpose health-monitoring tool that is also applicable to power generation and transmission system monitoring.

INTRODUCTION

Space transportation systems and launch site ground support systems are very complex, with a large number of sensors and many interactions between components. Monitoring the health of these systems under various operating conditions and detecting subtle system degradation is difficult. Various methods have been employed to assist operators with the monitoring task, including parameter limit checking, model-based systems, and rule-based systems. Parameter limit checking is in widespread use because of its simplicity. However, it requires significant operator training to interpret and respond appropriately to potentially large combinations of simultaneous alerts. Model-based and rule-based systems move much of the cognitive load from the operator to the computer by encoding the operation

of the system and automating some of the deductive reasoning an operator must perform. However, both model-based and rule-based systems require the manual extraction of system knowledge. Developing a model of a system requires significant effort to fully understand and accurately encode its internal operation. Developing a complete set of rules to correctly define nominal relationships among sensors under diverse operating conditions similarly requires significant effort. Data-driven monitoring techniques have been developed to address these issues.

Data-driven techniques are complementary to, but also have a number of advantages over, other methods for monitoring complex space vehicles and launch systems. Unlike model-based systems, the developer does not need to understand or encode the internal operation of the system. The knowledge required to monitor the system is *automatically* derived from archived system operations data. Unlike rule-based systems, data-driven systems do not require system analysts to manually define nominal relationships among sensors; the data-driven system *automatically* extracts relationships. Data-driven techniques are not limited to low-dimensional spaces and work as effectively with dozens of parameters as they do with a few. Furthermore, knowledge bases formed by data-driven techniques are easy to update. As the operating envelope of the monitored system is expanded, data-driven techniques can be quickly retrained to incorporate the new behavior into the knowledge base. The expertise and the time-consuming process of updating a model or rule base to maintain consistency with the new operation are not required.

There are numerous examples of data-driven systems, including systems that use support vector machines (SVM, reference 1, e.g., NASA Ames Research Center (ARC)'s Mariana), nearest neighbors (reference 2, e.g., Orca, cooperatively developed by ISLE and NASA), neural networks (reference 3, numerous, including Gensym's Neuronline), clustering (e.g., NASA ARC's IMS), hybrid (reference 4, e.g., NASA Jet Propulsion Laboratory's BEAM), as well as conventional numerical statistics. We will focus on one of these – IMS – in particular.

INDUCTIVE MONITORING SYSTEM (IMS)

The Inductive Monitoring System (IMS, references 5 – 7) is a general purpose, data-driven system health monitoring software tool that has been successfully applied to several aerospace applications and is under evaluation for anomaly detection of vehicle and ground equipment for next generation launch systems.

One powerful feature of many data driven anomaly detection techniques is the ability to simultaneously analyze multiple parameters. This feature allows them to discover and model interactions between related parameters that might be difficult to notice when monitoring the parameters individually. A basic data structure used for distance-based analysis is a vector of parameter values (Figure 1). Vectors containing *N* values are treated as points in an *N*-dimensional

Pressure A	Valve 1 Position	Pressure B	Valve 2 Position	Pressure C	Temperature 1	Temperature 2
2857.2	86.4%	1218.4	96.2%	1104.1	49.8	37.6

Figure 1: Sample data vector.

vector space. An appropriate distance metric is used to calculate the distance between these points. The familiar Euclidean distance metric has proven effective in many applications, though other metrics may also be useful. The underlying premise of distance-based anomaly detection is that anomalous data points will fall a significant distance away from typical, nominal data points.

For system health monitoring applications, vector parameters are typically instantiated with concurrent sensor values collected from a time slice of the data stream. Additional computed (derived) values or parameter values from previous data samples could also be included in the vector. For instance, increased system insight can often be obtained by incorporating values in the vector such as the rate of change of a pressure, the difference between two related temperature sensors, or the difference between commanded and actual values for a set point or actuator position. Also, augmenting the vector with values collected during previous time slices can implicitly capture short-term system operation patterns and trends. Flight controllers and engineers familiar with the monitored system can often suggest useful telemetry and derived parameters to use in the health monitoring vectors. Before processing, these vector values are typically normalized by applying z-score normalization or a similar method to each of the parameters.

IMS uses a data-driven technique called clustering to extract models of normal system operation from archived data. IMS works with vectors of data values, as described above. During the learning process, IMS analyzes data collected during periods of normal system operation to build a system model. It characterizes how the parameters relate to one another during normal operation by finding areas in the vector space where nominal data tends to fall. These areas are called nominal operating regions and correspond to clusters of nearby, similar points found by the IMS clustering algorithm. IMS represents these nominal operating regions as hyper-boxes in the vector space, providing a minimum and maximum value limit for each parameter of a vector contained in a particular hyper-box (Figure 2). These hyper-box cluster specifications are stored in a knowledge base that IMS uses for real-time telemetry monitoring or archived data (post-flight) analysis.

Pressure A	Valve 1 Position	Pressure B	Valve 2 Position	Pressure C	Temperature 1	Temperature 2
2860.1	86.9%	1222.4	97.2%	1105.3	51.8	39.6
2855.4	85.7%	1216.3	94.3%	1101.8	48.3	37.4

Figure 2: Sample IMS cluster hyper-box.

During the monitoring operation, IMS reads and normalizes real-time or archived data values, formats them into the predefined vector structure, and searches the knowledge base of nominal operating regions to see how well the new data vector fits the nominal system characterization. After each search, IMS returns the distance from the new vector to the nearest nominal operating region, called the composite distance. Data that matches the nominal training data well will have a composite distance of zero. If one or more of the data parameters is slightly outside of expected values, a small non-zero result is returned. As incoming data deviates further from the normal system data, indicating a possible malfunction, IMS will return a higher composite distance value to alert users to the anomaly. IMS also calculates the contribution of each individual parameter to the composite deviation, which can help identify and isolate the cause of the anomaly.

IMS SPACE APPLICATIONS

IMS has been deployed in NASA mission control to support real-time telemetry monitoring and has generated interest in data-driven monitoring capability for other NASA programs. Several projects were undertaken to mature the IMS technology and complementary tools for use in NASA's Constellation program, including pre-launch ground diagnostics for NASA's Ares I-X development flight test and Ares I ground support equipment health monitoring.

INTERNATIONAL SPACE STATION

NASA's International Space Station (ISS) flight control team is responsible for fault management activities. To assist with this task, IMS has been deployed in support of two flight control disciplines: attitude control and thermal operations. The Attitude Determination and Control Officer (ADCO) monitors, among other systems, the Control Moment Gyroscope (CMG) and Rate Gyro Assembly (RGA) systems. The Thermal Operations (THOR) officer monitors the External Thermal Control System (ETCS) as well as other related systems.

The ISS Control Moment Gyroscope (CMG) attitude control system consists of four large gyroscopes, each mounted in a gimbal system that can rotate the CMG about the two axes perpendicular to the gyroscope spin axis (Figure 3). The CMGs operate as non-propulsive attitude control devices that exchange momentum with the ISS through induced gyroscopic torques.

Figure 3: ISS Control Moment Gyroscopes.

As they have aged, some of the CMGs have degraded enough to malfunction and require replacement. Given their history, the ADCO flight controllers are interested in detecting early symptoms of degradation in the CMGs.

Working with ADCO flight controllers, nine telemetered and four derived CMG parameters were selected for real-time monitoring. Seven to ten months of archived data was analyzed for each of the four CMGs. The data was sampled at a 1 Hz rate, formed into vectors of 13 values, and four IMS monitoring knowledge bases were constructed from the collected data. Each CMG was analyzed individually to capture its unique characteristics.

The IMS monitoring application was integrated with the NASA Mission Control data server software to access real-time telemetry in the ISS flight control room. Four IMS processes, one per CMG, run on the ADCO flight control console to provide continuous real-time monitoring. Once per second, each process compares incoming telemetry data with the appropriate CMG knowledge base and returns the amount of overall deviation, if any, from the nominal training data. It also returns the contribution of

each individual parameter to any deviation to aid in isolating the source of the deviation. These IMS results are published back to the Mission Control data server for access and monitoring by other Mission Control software applications. IMS composite distances are plotted on ADCO console displays and automated alerts issued if significant deviations occur.
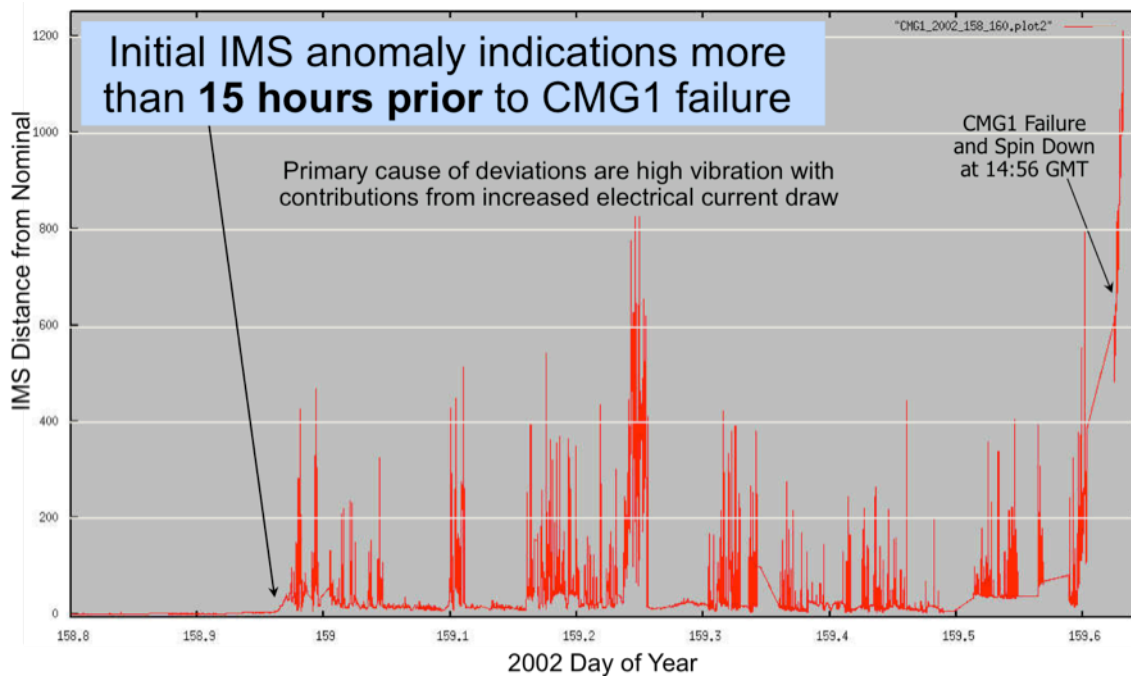
Figure 4: ISS Control Moment Gyro (CMG) failure. IMS detected failure symptoms 15 hours prior.

Figure 4 shows an example from the monitoring of one of the CMGs. IMS detected precursor failure symptoms, as evidenced by the sudden jump in "Distance from Nominal" values, more than 15 hours before the eventual failure and spin down of the gyroscope occurred.

Successful deployment and certification of the IMS CMG monitoring system led to further development of real-time data-driven monitoring for ISS subsystems. The IMS CMG application was generalized to accept an arbitrary number of user-selected input parameters and to run on any controller console in the ISS flight control room. The resulting tool, called AMISS for Anomaly Monitoring Inductive Software System, has been applied to the
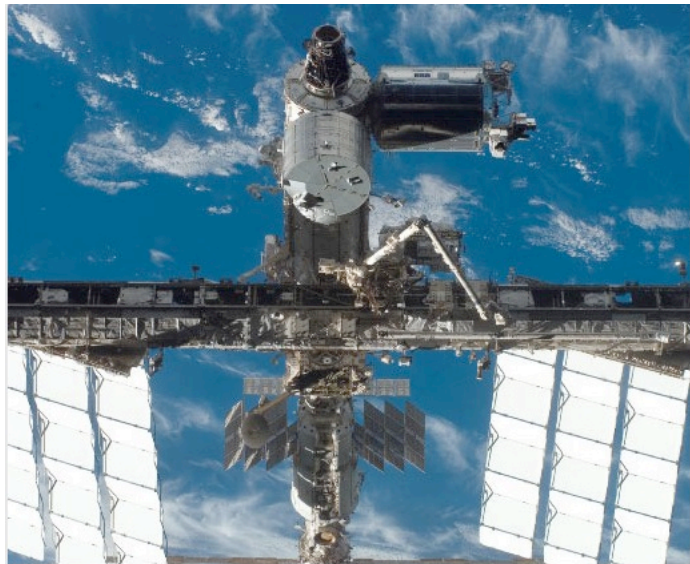
Figure 5: ISS external view showing ETCS radiators at lower left and lower right.

thermal operations (THOR) domain, monitoring subsystems of the ISS External Thermal Control System (ETCS).

The ETCS is used to dissipate heat onboard ISS. Excess thermal energy from inside the ISS is transferred to liquid ammonia cooling loops in the ETCS. The heated ammonia is then circulated to radiators and cooled as thermal energy is released into space (Figure 5). ETCS systems are separated into two independent loops with three major subsystems each: the Pump Module (PM), the Ammonia and Nitrogen Tank Assemblies (ATA/NTA), and the Radiators (RAD). The PM circulates coolant through the ETCS, the ATA/NTA stores reserve ammonia coolant and maintains pressure within the ETCS systems, and the RAD system controls the flow of coolant to each of three thermal radiators.

AMISS knowledge bases were constructed from a year of archived ETCS operational data, one knowledge base for each major ETCS subsystem, and two knowledge bases covering all pertinent parameters in each ETCS loop. The subsystem modules monitor for anomalies that occur within each subsystem while the full loop modules also watch for anomalies that are only apparent in subsystem interactions.

Figure 6 shows an example of an anomaly detected by IMS/AMISS in an early configuration of the ETCS. In early January 2007, the ISS EETCS (Early External Thermal Control System) developed an ammonia gas bubble in the normally liquid ammonia lines. Off-line IMS analysis after the event was able to detect the bubble as it began to grow, approximately six days prior to the bubble being detectable by standard telemetry monitoring methods. Using traditional monitoring, the controllers detected the anomaly nine hours before the bubble "burst" and dissipated back into liquid.
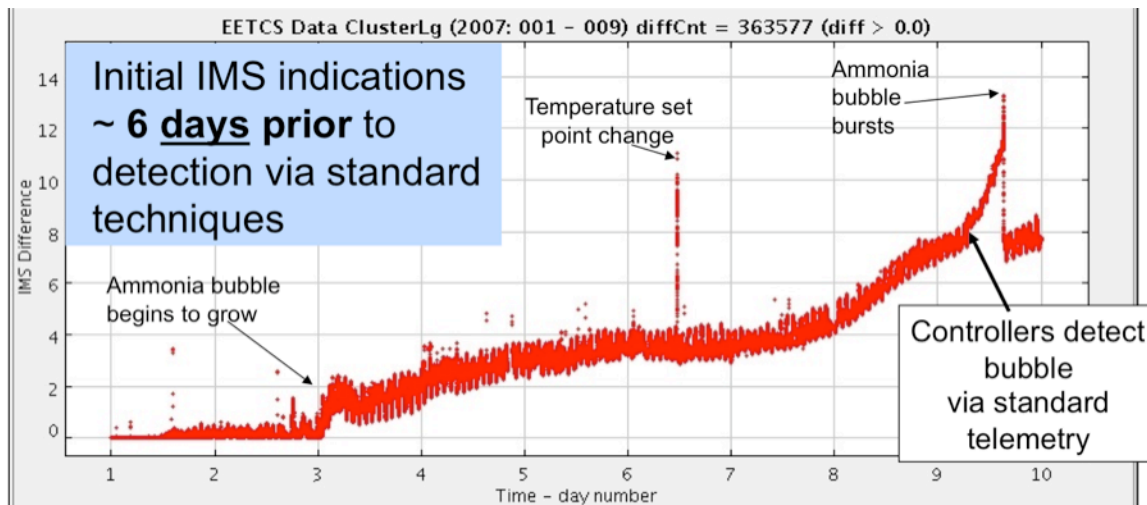

Figure 6: ISS External Thermal Control System anomaly. IMS detected the anomaly six days prior.

CONSTELLATION PROGRAM

NASA's Constellation Program, part of President Bush's 2004 Vision for Space Exploration, aims to return man to the Moon and then venture to Mars and beyond. To accomplish that goal, NASA is

developing three new vehicles – the Ares I crew launch vehicle, the Ares V cargo launch vehicle, and the Orion crew exploration vehicle. To support these vehicles, NASA is also updating the ground support equipment (GSE) necessary to support such operations as transporting, receiving, handling, assembly, inspection, test, checkout, servicing, launch, and recovery of space systems. As of this writing, the Constellation program is in jeopardy and may be cancelled. However, the concepts presented here are expected to be applicable to the space vehicles and the necessary upgrades of NASA's launch complex for future programs.

IMS has been demonstrated for anomaly detection for both Ares I-X (the test flight of Ares I, as described below) and ground support equipment.

ARES I-X

Ares I-X was the first uninhabited test flight of Ares I (reference 8). It launched on October 28, 2009 (see Figure 7). The Ares I-X Ground Diagnostic Prototype (GDP, reference 9) is a prototype ground diagnostic system that provided anomaly detection, fault detection, fault isolation, and diagnostics for the Ares I-X first-stage Thrust Vector Control (TVC) and for the associated ground Hydraulic Support System (HSS) while the vehicle was in the Vehicle Assembly Building (VAB) at Kennedy Space Center and while it was on the launch pad. The TVC is used to steer the vehicle during ascent by moving the nozzle of the first-stage solid rocket booster. The HSS provides hydraulic pressure for testing the TVC before launch. GDP is intended to serve as a prototype of a future operational ground diagnostic system for Ares I or other future launch vehicles.

The prototype combines three existing diagnostic tools: TEAMS, SHINE, and IMS. TEAMS (Testability Engineering and Maintenance System) is a model-based tool that is a commercial product from Qualtech Systems Inc. It uses a qualitative model of failure propagation to perform fault isolation and diagnostics. GDP integrated TEAMS models of the TVC and of the ground hydraulics to provide integrated fault isolation of both systems. SHINE (Spacecraft Health Inference Engine, reference 10) is a rule-based expert system that was developed at the NASA Jet Propulsion Laboratory.

Figure 7: Ares I-X launch from Kennedy Space Center, October 28, 2009.

SHINE rules were developed both for fault detection and operating mode identification. The prototype uses the outputs of SHINE as inputs to TEAMS. Finally, IMS was used for anomaly detection in parallel with the TEAMS/SHINE combination. The expectation was that TEAMS and SHINE would detect all of the known failure modes that were modeled, while IMS would have the potential to detect unknown failure modes and anomalies that are not yet failures.

Because the Ares I-X TVC and HSS are very similar to the corresponding systems on Shuttle, IMS was trained on historical Space Shuttle data and tested on historical Shuttle data into which simulated failures were inserted. During the Ares I-X pre-launch period, IMS used this knowledge base to process Ares I-X data while the vehicle was in the Vehicle Assembly Building (VAB) and at the launch pad.

IMS flagged three periods of anomalous behavior for the Ares I-X data gathered in the VAB and fewer at the launch pad. In each case, analysis confirmed that the anomalies were caused by operational differences between Shuttle and Ares I-X. For example, differences in how actuator tests are performed in Ares I-X vs. Shuttle caused false alarm 1, shown in Figure 8. In recent years, the TVC actuator tests performed in the VAB have all been "pinned" tests, meaning that the actuator is physically pinned to the nozzle during testing, so that the nozzle moves during the test. The first TVC actuator position test performed in the VAB for Ares I-X was an "unpinned" test, meaning that the
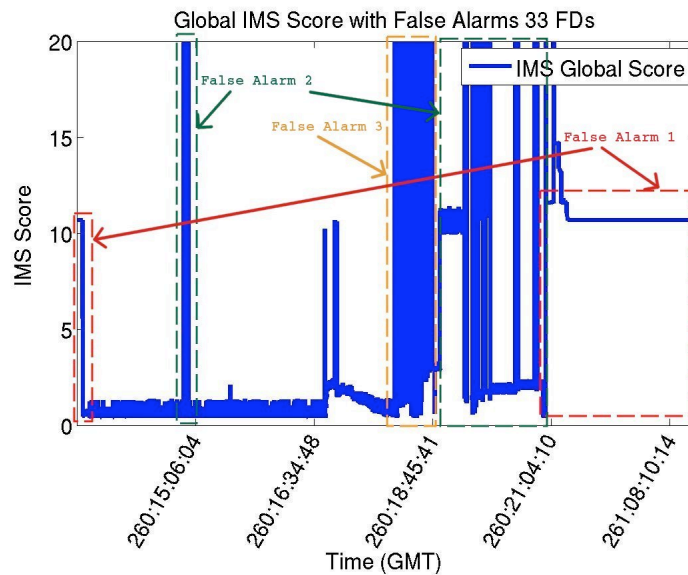
Figure 8: IMS scores for Ares I-X Sept. 17, 2009 VAB operations. Periods during which IMS detected anomalies that were not failures are labeled as "false alarms" and were caused by differences in operation between Shuttle (the training data set) and Ares I-X.

actuator was detached from the nozzle, and the nozzle did not move during the test. Because the actuator was unpinned, it was able to move through a larger range of motion that is not possible during pinned testing. IMS therefore saw position values that it had never seen in the Shuttle data, which it flagged as anomalies. These anomalies are "false alarms" in the sense that they are not failures. However, they do illustrate the ability of IMS to detect new data that is different from what it has seen before. Training on operational data from the vehicle being monitored would eliminate this issue of flagging nominal operating behavior as anomalous; it would flag only behavior that differs from the data on which it was trained.

GROUND SUPPORT EQUIPMENT

Another prototype for using IMS for anomaly detection was developed for the liquid hydrogen (LH2) Ground Support Equipment (GSE) used to fill and drain the vehicle fuel tank, with the expectation that next generation launch vehicles will also have liquid-fueled engines. For demonstration purposes, we trained IMS on Shuttle data. One such demonstration involved an LH2 leak at the Ground Umbilical Carrier Plate (GUCP) – which is the interface of the External Tank (ET) and the hydrogen vent line – on Space Shuttle mission STS-119 in March 2009 and then again on STS-127 in July 2009. On both missions, during the final stages of loading LH2 ("LH2 tanking") into the ET, sensors measured a significant leak near the GUCP, leading to launch scrubs. Figure 9 shows the data for some of the relevant parameters for LH2 tanking.

For the demonstration, we trained IMS on two configurations of the same data set from a single nominal tanking (from the final tanking prior to the launch of STS-119). In one configuration, we used
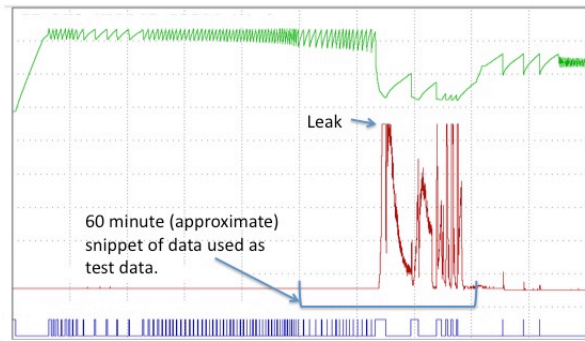
Figure 9: LH2 tanking data. The red plot (middle) shows the measurements from a GUCP-local leak detection sensor. The green plot (top) shows an ullage pressure measurement. The blue plot (bottom) shows a discrete vent valve open indicator. Approximately six hours of data is shown.

all seven LH2 system parameters. In the other, we used just four parameters, eliminating a discrete valve-open indicator and two parameters indicating local H2 concentration (the leak detectors). The remaining four parameters included two pressure parameters and two temperature parameters. The test data set was from the off-nominal STS-119 tanking. The IMS composite deviation scores (i.e., the distance or deviation from a test set data vector to the nearest nominal cluster) for the seven-parameter configuration are shown in Figure 10 and the composite deviation scores for the four-parameter configuration are shown in Figure 11. Notice the similarity of the shape of the seven-parameter IMS composite deviation score to the tanking data

shown in Figure 9. The score is very closely tracking the leak detector measurement. The deviation score increase corresponds exactly with the leak detector increase. Note that even after removing the leak detectors from the data set, IMS continues to indicate anomalous behavior, though a bit delayed and not quite as strong as the indications from the full vector. This highlights IMS's ability to detect off-nominal states even when direct measurements are not available.
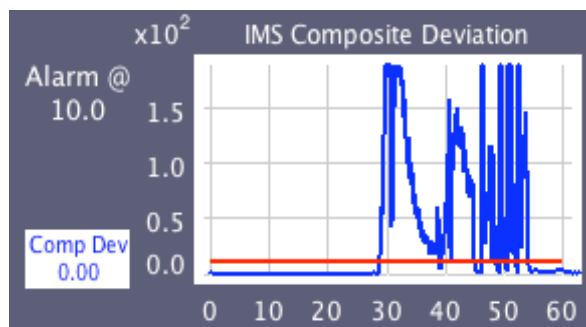
Figure 10. IMS composite deviation score for STS-119 off-nominal data set trained on seven parameters. One hour of data is shown. The red line represents the alarm threshold. It is user-settable in the GUI.
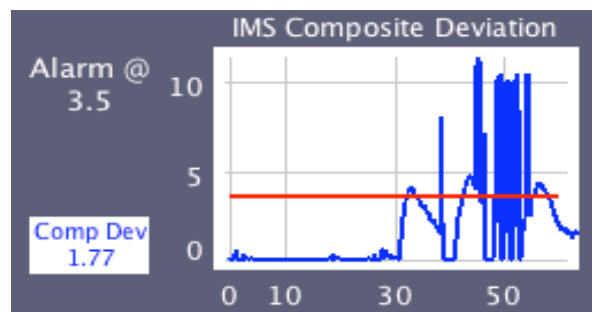
Figure 11. IMS composite deviation score for STS-119 off-nominal data set trained on four parameters. One hour of data is shown (same period as in Fig. 10). As in Figure 10, the red line is the user-settable alarm threshold.

CONCLUSIONS

Through practical application, it has been demonstrated that data-driven system health monitoring, such as performed by the Inductive Monitoring System (IMS), can be useful in a variety of space mission operations settings. Furthermore, data-driven methods can complement other data analysis and diagnosis tools, together providing integrated system health management and fault recovery recommendations. A number of NASA projects incorporating data-driven anomaly detection have

been deployed or are under development. The emergent projects will provide proof of concept demonstrations by combining data-driven techniques with model-based and rule-based software tools for fault management. They will also produce recommendations on which types of systems would most benefit from data-driven and integrated data-driven, rule-based, and model-based approaches for fault detection and health management. This information will help guide NASA as it builds operations and ground support systems for next-generation space programs as well as providing guidelines for commercial and other government applications for the technologies. In particular, the lessons learned from applications to space operations directly transfer to application of IMS by the power industry.

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