Model-based safety assessment for safety critical system

by

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Model-Based Safety Assessment of Safety Critical Systems

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NOWADAYS, MODEL-BASED DIAGNOSIS PLAYS AN IMPORTANT ROLE IN MANY SYSTEMS FROM SIMPLE TO COMPLEX, ESPECIALLY SYSTEMS WITH HIGH DEMAND OF SAFETY. IN AVIONICS/AEROSPACE SYSTEMS, THE LARGE DISTANCE FROM THE VEHICLE TO EARTH MAKES THE MAINTENANCE PROCESS DIFFICULT. AS A RESULT, IN THIS FIELD MODEL-BASED DIAGNOSIS HAS BECOME A MAJOR METHOD FOR FAULT IDENTIFICATION AND RECOVERING AND NASA AMES RESEARCH CENTER HAS DEVELOPED THE ADVANCED DIAGNOSTICS AND PROGNOSTICS TESTBED (ADAPT) AS A PLATFORM FOR EXPERIMENTING AND COMPARING THE RESULTS OF DIFFERENT DIAGNOSIS TECHNOLOGIES AND TOOLS.

This study reviews the theory of model-based diagnosis and how it is employed in avionics systems. The diagnosis system in our study consists of a set of sensors monitoring different parameter of electrical components in the system to detect and locate faults. In the scope of this study, we focus on detecting drift fault of electrical components’ parameter such as values of voltage, current and resistor. Two approaches are used for detecting this kind of fault: CUSUM chart V-mask method and Shewhart variable control chart. The application which is built based on these approaches will be run on ADAPT and the result will be showed and discussed.
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TABLE OF CONTENTS

ABSTRACT ..................................................................................................................................................2
ACKNOWLEDGEMENT ............................................................................................................................3
ABBREVIATION LIST ...............................................................................................................................6
LIST OF FIGURE .........................................................................................................................................7
1. INTRODUCTION .....................................................................................................................................8
   1.1. Background .......................................................................................................................................8
   1.2. Objectives ........................................................................................................................................8
   1.3. Scope of study ...................................................................................................................................8
   1.4. Planned Tasks ...................................................................................................................................9
2. THEORY BASE ......................................................................................................................................10
   2.1. Model-based diagnosis ......................................................................................................................10
       2.1.1. Fault detection and diagnosis methods .....................................................................................10
       2.1.2. Principles of Model-based diagnosis .......................................................................................10
   2.2. CUSUM ..........................................................................................................................................15
       2.2.1. CUSUM method ........................................................................................................................15
       2.2.2. CUSUM-chart plot detection method .......................................................................................17
       2.2.3. CUSUM-chart V-Mask method ................................................................................................17
       2.2.4. Other CUSUM-chart methods ..................................................................................................19
   2.3. Shewhart ........................................................................................................................................20
       2.3.1. Variables Control Charts .........................................................................................................20
       2.3.2. Other Shewhart chart methods .................................................................................................21
3. ADVANCED DIAGNOSTICS AND PROGNOSTICS TESTBED (ADAPT) .............................................22
   3.1. General description ..........................................................................................................................22
   3.2. System detail ...................................................................................................................................23
Model-Based Safety Assessment of Safety Critical Systems

3.2.1. Power generation unit ................................................................. 24
3.2.2. Power storage unit ................................................................. 24
3.2.3. Power distribution unit ............................................................. 25
3.2.4. Control and monitor ................................................................. 25

4. IMPLEMENTATION ........................................................................... 26

4.1. Fault types in DXC’10 industrial track ................................................. 28
   4.1.1. Drift .................................................................................. 28
   4.1.2. Other fault types ................................................................. 29

4.2. Early drift fault detection application .................................................. 29

5. EXPERIMENT RESULTS AND CONCLUSION ..................................... 30

5.1. Experiment results ........................................................................ 30

5.2. Conclusion ................................................................................ 35

REFERENCES ...................................................................................... 36
ABBREVIATION LIST

- ADAPT: Advanced Diagnostics and Prognostics Testbed
- CUSUM: Cumulative sum control chart
- EPS: Electrical power system
- HLC: Higher control limit
- LLC: Lower control limit
- DC: Direct current
- AC: Alternative current
- API: Application protocol interface
LIST OF FIGURE

Figure 2.1: A general model-based diagnosis system example…………………12
Figure 2.2: Simple multiplier-adder system, taken from [1]…………………………12
Figure 2.3: Simple multiplier-adder system, M1 OR A1 is defective. Taken from [1]..13
Figure 2.4: Simple multiplier-adder system, M2 AND A2 are defective. Taken from [1]…………………………………………………………………………………14
Figure 2.5: Sequence of time-series random example data. Taken from [3]…………16
Figure 2.6: CUSUM plot chart of the data set in Figure 2.5. Taken from [3]………..16
Figure 2.7: Visual form of CUSUM-chart V-Mask. Taken from [7]…………………19
Figure 3.1: ADAPT lab at Ames Research Center. Taken from [10]………………..23
Figure 3.2: Testbed components and interconnections. Taken from [11]…………..24
Figure 4.1: ADAPT-Lite – Diagnostic Problem 1 from [13]………………………….26
Figure 4.2: ADAPT – Diagnostic Problem 2 from [13]……………………………….27
Figure 4.3: Fault types in DXC’10, taken from [13]……………………………………..28
Figure 4.4: Drift fault profile, taken from [13]…………………………………………..28
Figure 5.1: Shewhart chart for drifting component IT267…………………………….34
Figure 5.2: CUSUM chart for drifting component IT267…………………………….34
1. INTRODUCTION

1.1. Background

Technology is developing very fast in recent years and along with it, the complexity of different systems deployed to serve varied demands of human society is increasing significantly. The bigger and the more complex they are, the higher risk they can have errors in different components which could lead to system failure. It is vital for a system to guarantee that it functions correctly during its lifetime with reasonable maintenance cost. Different safety assessment standards are invented, which go through different stages such as functional hazard analyses, preliminary fault tree analysis, common cause analysis, failure mode and effect analysis in order to derive all the safety requirements. Among modern safety assessment methods, model-based diagnosis is becoming more and more popular and it is proving itself to be an efficient method for safety and diagnosis system design as well as providing effective traceability in safety assessment process.

1.2. Objectives

The aim of this study is to have a thorough understanding of model-based diagnosis. A module of a diagnosis system will be implemented as a part of a model-based diagnosis system performing on the NASA’s Advanced Diagnostics and Prognostics testbed (ADAPT). The module is called “Preliminary data filter” which performs the task of drift fault early detection. 2 algorithms are used to build this module: CUSUM and Shewhart.

In order to achieve the aim above, 2 research questions need to be solved:

- Research question 1: What method can be used for early detection of drift fault in model-based diagnosis?
- Research question 2: Which algorithm can detect drift fault in the shortest time with reasonable accuracy particularly for NASA’s ADAPT system?

1.3. Scope of study

The study presented in this thesis has some limitations:

- The study presented in this thesis covers the theory of most ideas of Model-based diagnosis but the implementation is only in one part of a model-based diagnosis system performing on NASA’s ADAPT platform.
- The data for performing diagnosis is the sample data in context of the Second Diagnostics Competition DX-10.
Model-Based Safety Assessment of Safety Critical Systems

- The full diagnosis system is generally described but not in detailed and the integration part between the Preliminary data filter module and the remaining parts of the system has not been developed.

The solutions for the limitations above are considered as future work after finishing this thesis.

1.4. Planned Tasks

This thesis covers the tasks below:

- Thorough presentation about Model-based Diagnostic and NASA’s Advanced Diagnostics and Prognostics testbed (ADAPT) platform.

- Detailed description of CUSUM and Shewhart algorithms.

- Implement the Preliminary data filter module of the diagnosis system performing on ADAPT.

- Compare the results of different algorithms used in the module and discussion.
2. THEORY BASE

2.1. Model-based diagnosis

2.1.1. Fault detection and diagnosis methods

In recent years, a significant speed of development has been recorded for fault detection and diagnosis methods for technical systems. From the demand to reduce the maintenance cost and improve quality and reliability of systems from simple to complex, from the fact that components in every system always have a certain possibility to have defects during runtime, causing unexpected behaviors or a breakdown of the whole system. The main objectives of diagnosis are to detect the faults and to identify the cause of it. Diagnostic methods in general work basing on the characteristic value of all or some components in the system. These values are monitored by a sensor system during runtime. There are some diagnostic methods which are widely used not only in research environment but also in real systems in the industry:

- Rule-based diagnostic method: can be considered as “learn from experience”. A set of cases are collected and stored in the diagnostic system and will be used as the knowledge to make the diagnosis. Since all the cases are provided in advance, the processing time of this method is short and less resource is consumed.

- A range of “acceptable” values is identified for the values of components. If the value of the component at some points in time falls out of this range, the component is considered defected and the system is out of control.

- Redundant function: using more than 1 sensor to monitor the same set of components. Since the sensor can also be broken and this method can distinguish between sensor failure and components failure, it is used in critical systems which require high level of safety.

- Model-based diagnosis: this is the method we take into consideration and use in the implementation application of this thesis. It will be covered in the next part of this chapter

2.1.2. Principles of Model-based diagnosis

The general idea of this method is to build a model of the observed system. Once the model is built, a simulation of how the real system works can be performed on this model. The behavior of the real system is monitored and compare with the behavior of the “ideally correct” model, which is the result of the simulation above. If the difference between these 2 values exceeds a threshold which is decided basing on the
characteristics of the system, it is an indication that the system is faulty. Diagnosis process in model-based diagnosis consists of 2 steps:

- Detecting the faults and identifying the faulty components in the model.
- Explain the faults.

Thorough analysis of the deviations between the predicted behavior from the model and the actual behavior of the system can be carried out by the diagnosis engine (or sometimes called diagnosis reasoner) to achieve the result of the diagnosis. Different algorithms are developed to be used in different model-based diagnosis systems to carry out diagnostic tasks automatically. In addition, actions might be proposed by the diagnosis method to fix the problem or avoid the system failure.

A model system in model-based diagnosis consists of a set of model components. Different sets of model components (component model library) are used in different model-based diagnosis engine to build corresponding model systems. Each component model library obey a set of law according to the characteristics of the corresponding real system. For instance, an electrical circuit can be modeled by a component model library which consists of model of electrical components and the model-based diagnosis engine which controls and monitors the model system. Each component in the library works correctly following the theory of electricity and physics, etc., i.e. the resistor works according to Ohm’s law. The model components and the model-based diagnosis engine are generic, they are not defined for any specific system but instead present the behavior of the corresponding component in any system. Every system consists of the components among the library can be modeled and diagnosed by the component model library and the model-based diagnosis engine. As the result, different model systems with the same component model library can be combined together or a model can be split up into several smaller models.

Figure 2.1 depicts how model-based diagnosis method works in general. The real system consists of different components and the model system has corresponding models for the components. Model-based diagnosis engine guarantees that all the model components work in the same way as the real components do in any system. The same input A is provided for both 2 systems, the results monitored from the real system and the model system are X and Y, respectively. In the normal case, the results of these 2 systems should be consistent, or the difference should be reasonably small. If the difference between X and Y exceeds a threshold value T, the real system is considered faulty. Further analysis will be carried out to identify which components are faulty. An illustration of this analysis will be presented in the next example.
Figure 2.1: A general model-based diagnosis system example

The process of comparison and analysis the results of the simulation over the model and the observed behavior of the real system is performed by a reasoning engine. The reasoning process is depicted by the following example taken from Peter Bunus and Karin Lunde, 2008 [1]

Figure 2.2: Simple multiplier-adder system, taken from [1]

There are overall 3 multipliers: M1, M2, M3 and 2 adders: A1, A2 in the system. The inputs are A = 3, B = 2, C = 2, D = 3, E = 3. X, Y, Z are the outputs of M1, M2, M3, respectively, then become the input for A1, A2. The outputs F and G in the system are monitored. The results of the calculations can be done by an inference engine. If the system works correctly, X = 6, Y = 6 and Z = 6, then F and G will be equal and = 12.
Due to the characteristics of the system which is integer calculations, any inconsistency between the inference engine’s prediction and the monitored result made by the real system can be considered a fault. Assume that \( F = 10 \) and \( G = 12 \) are the results observed from the system, there is a difference between the expected value of \( F = 12 \) and the actual value \( F = 10 \). This difference is observed by the diagnostic engine of the system. The first step of model-based diagnosis: “detect the fault” has been done.

Moving on to the next stage, the model-based diagnosis engine will give the explanation to the problem detected. In other words, in this particular case, possible defective components will be pointed out. 2 possible cases are given in Figure 2.3 and Figure 2.4.

![Diagram](image)

**Figure 2.3:** Simple multiplier-adder system, M1 OR A1 is defective. Taken from [1]

In Figure 2.3, the cause for the wrong result \( F = 10 \) comes from either the multiplier M1 or the adder A1 fails to give the correct output. This conclusion bases on the fact that the output \( F \) depends on 3 components: M1, M2 and A1. M1 and M2 provide the inputs X and Y for A1 to produce the output \( F \). As the result, both of these 3 components may be defective. However, M2 also provides an input for A2 and the output \( G = 12 \) of A2 is correct. With the assumption for now that only 1 component can be faulty at a time, we have the possibility that M1 or A1 is defective.
In Figure 2.4, we consider not only 1 component can be faulty. With this multiple defective components case, abductive reasoning can be used to find the set of possibly defective components. Abductive reasoning is a logical inference by Charles Sanders Peirce, basing on the initial set of assumptions to produce a set of hypotheses to explain the phenomenon. These hypotheses might be proven to be wrong if other related information comes up proving the contradiction. In our particular case of Figure 2.4, to exclude first candidate set we pointed out in Figure 2.3, assume that M1 and A1 work properly. The only one component can cause the wrong output of F is M2, so M2 must be defective. However, M2 also provides Y as the input for A2 and the output G = 12 of A2 is correct. If M2 is faulty, which means Y has to be different from the correct value it should be (6), then there are 3 possible sub cases:

- A2 should be faulty so with the wrong input, by accident it provides the correct output G.
- M3 should be faulty so it compensate for the wrong result of M2 to make up the correct value G
- Both M3, A2 are faulty and by coincident, they make up the correct output of G = 12.

In our current situation without any further information about the value of Y, Z, we accept the 3 hypotheses above. Figure 2.4 illustrates the first sub case: M2, A2 are defective at the same time.

In more complex systems where the input and the output are not integer numbers as above but can be a stream of signal, more sophisticated reasoning methods are
employed in the diagnosis process. 2 algorithms used in the implementation part of this project will be presented in the following parts of this chapter.

2.2. CUSUM

As we know from the previous parts of this study, model-based diagnosis’ general idea is to detect and analyze the differences - if there is – between the results of the real system with the predicted results of the model of the system. According to [2], Model-based diagnosis systems can use traditional general purpose programming language or specialized modeling language such as declarative equation based language Modelica to build their models. When the system consists of a set of electrical components, the results of the system can be the value of voltage, current and resistance given by sensors which are placed inside the system. We assume that all these values are stable during the time the system works. The values monitored by the sensors are regularly sent to the diagnosis system, the observed behavior of the system here is a time-series of values and it can fluctuate over time, so sequential changes is essential to be detected [3]. When the value of one component changes and goes out of a defined threshold, we consider this is a fault, the component is defective and the system goes “out of control”. The problem here is how to detect faults correctly and as early as possible. 2 methods are chosen to build the fault-detection module: CUSUM and Shewhart (Shewhart will be presented in the next part of this chapter). The description of these 2 methods is the answer for the research question 1 of this project, CUSUM and Shewhart are suitable methods to use for early detection of drift fault in model-based diagnosis.

2.2.1. CUSUM method

CUSUM (Cumulative sum) is a sequential analysis technique which can be used to detect changes in a sequence of values, and this is the main purpose for using CUSUM in this study. Originally, CUSUM statistics are developed for detecting the signal from the background noise. Assume that at one point in time, the expected signal deviates from the background noise (onset time) and at one point of time later disappears (offset time), CUSUM statistics should be able to detect and extract it from the background noise which also randomly fluctuates itself. In case of the electrical system example we mentioned above, consider the fault occurrence for a component is the expected signal and the normal (correct) characteristic values of the component as the background noise, CUSUM fits our requirement for detecting the fault occurrence during working time of the component.

A very good review of CUSUM method is presented in [3]. We suppose the input data set is a sequence of data points \{a_{-n}, a_{n+1}, \ldots, a_{-1}, a_0, a_1, \ldots, a_n \}. This sequence can be considered as a discrete stream of data observed at the point of time t, with t in \{-n, -n+1, \ldots, 0, 1, \ldots n\}. A set of example data is illustrated in Figure 2.5.
The CUSUM at the point of time $t$ is calculated with the formula (taken from [3]):

$$c_t = \sum_{i=1}^{t} a_i$$

Apparently, with a relatively stable set of input data and the assumption that $a_i \geq 0$, $c_t$ is a monotonically increasing function. The figure of CUSUM $c_t$ with the data set from Figure 2.5 is depicted in Figure 2.6.

If there is any big change from the input data, the CUSUM slope will become shallower or steeper. In a more general case when $a_i$ is a real number, $c_t$ is not necessarily like above. But the case we are interested in is how to implement the Preliminary data...
filter module of the diagnosis system performing on ADAPT (ADAPT system will be presented in the next chapter), in which all components are electrical devices with the characteristic property values such as voltage, current, resistance $> 0$, so the example above, even though not absolutely generalized, fits the context of this project.

Different CUSUM methods have been developed and can be applied for detecting faults in our project. We will go through 2 typical methods.

**2.2.2. CUSUM-chart plot detection method**

CUSUM chart plot detection method was presented in [6]. In this method, a constant $k$ is identified as the mean of the set of data at the beginning of runtime. CUSUM values in CUSUM-chart plot method is calculated as below (the equation taken from [3]):

$$C_t = \sum_{i=1}^{t} (a_i - k)$$

If $a_i = k$, $C_t$ is always $= 0$. Another important parameter of this method is the threshold or the “alarm value” $h$. This is the value which is estimated from the beginning basing on the characteristics of the system so when $C_t$ exceeds $h$ ($C_t > h$), the system will be warned that the deviation is increasing a great deal and the system is now “out of control”. We can say $h$ is the criteria for the detection of deviation in CUSUM-chart plot method.

There are 2 kinds of test can be performed with CUSUM-chart plot method:

- One-sided test to detect the event when the value $a_i$ becomes larger than the mean $k$. In other words, it is called positive deviations compared to $k$ and the function $C_t$ would move upward. This one-sided test only for detecting positive deviations, so when $a_i$ becomes smaller than $k$, $C_t$ moving downward and when $C_t$ is lower than 0, the time resets. The duration between the starting time and that point is the run length. The run length depends both on the “window of data” – the set of data from the starting point of time until the reset time and also the starting time

- Two-sided test can detect both negative and positive deviations. This test can be carried simply by performing at the same time 2 one-sided test for detecting positive deviations and negative deviations.

**2.2.3. CUSUM-chart V-Mask method**

In CUSUM-chart plot detection method, the optimal value of threshold $h$ can only be identified correctly when we have full knowledge about the process. However, normally we do not have enough information regarding the process then $h$ is only estimated basing on an “average run length”. The value of $h$ for this reason can be too
Model-Based Safety Assessment of Safety Critical Systems

large, which might result in the case that the alarm is trigger too late, or too small, which might result in false alarm – the alarm is triggered when the deviation is still under control. This problem can be overcome by the V-Mask method.

As we noticed from the previous part of this chapter, if there is a “drift” in the value of the data sequence, the mean will change, resulting in the CUSUM chart going upward or downward following the shift of the mean. The problem is how to determine whether the deviation is out of control or not. V-Mask method gives us the answer for this question. There are 2 forms of CUSUM-chart V-Mask method:

- Visual form.
- Tabular form.

The tabular form of V-Mask, which is more popular in practice, will be used in the implementation part of this project. However, we will go through the theory of both these 2 forms.

The visual form is illustrated in figure 2.7. It can be seen as a horizontal V on the CUSUM graph. Some important elements of the form can be noticed:

- Origin: the V-Mask’s origin point is the latest CUSUM point recorded.
- The distance k and the rise distance h: these parameters are the V-Mask’s designed parameter, on which the result of the method mainly depends. The process to construct a V-Mask manually is complicated in practice. This is the reason why the tabular form of CUSUM-chart V-Mask is more popular and more widely used in practice.
- An alternative set of designed parameters for k and h is d and the vertex angle, it can be used to build the same V-Mask.
- All the CUSUM points before the origin point are supervised by V-Mask. The process is still under control if all those points lie inside the V shape. If one of them lies outside, the alarm can be triggered and the process is considered “out of control”. The CUSUM chart in Figure 2.7 illustrates an out of control situation since 1 point lies above the V shape.
The tabular form (or also called spreadsheet form) of CUSUM V-Mask is not as intuitive as the visual one presented above, but it is much easier to construct and more convenient to calculate and process in a real life computer program, e.g. implemented by spreadsheet software. As the result, it is preferred in practice.

The calculation of V-Mask’s tabular form also bases on the designed parameters $h$ and $k$. The main calculation is below:

$$Sh(i) = \max(0, Sh(i-1) + xi - \mu(0) - k)$$

$$Sl(i) = \max(0, Sl(i-1) + \mu(0) - k - xi)$$

$\mu(0)$ is the expected mean of the data sequence, $xi$ is the data value i in the data sequence. The values of $Sh(0)$ (higher) and $Sl(0)$ (lower) are 0. When either $Sh(i)$ or $Sl(i)$ is larger than $h$, it is corresponding to the CUSUM point lies outside the V shape in the visual form and the process is considered out of control. The implementation and result of this form will be showed in chapter 4 of this report.

2.2.4. Other CUSUM-chart methods

Beside the above 2 methods, there are also other CUSUM statistical detection methods which are widely used in medical or quality control systems. They can be studied further as the future work after this thesis project:
Model-Based Safety Assessment of Safety Critical Systems

- Cumulative observed expected (O-E) plots. Detail of this method can be found in [4].
- Requesting sequential probability ratio (RSPRT) charts. Detail of this method can be found in [5].
- CUSUM-slope: a statistical method to estimate the “average signal content” in a number of time windows [3]

2.3. Shewhart

Shewhart control chart was introduced by Walter A. Shewhart as a general model of control charts. The basic parameters and abbreviations are presented along with this control chart.

2.3.1. Variables Control Charts

Assume that w is the data points received from a data sequence of interest. The mean of all values of w which have been received is \( \mu \). Assume that there is a change in the values of w, the standard deviation of this change is \( \sigma \). The Higher control limit (HCL) and the Lower control limit (LCL) are calculated by the formulas below, according to [8]:

\[
\text{HCL} = \mu + k \sigma \\
\text{LCL} = \mu - k \sigma \\
\text{Center line} = \mu
\]

The constant \( k \) is the distance from the mean value to the control limits. In practice it is normally assigned to the value 2.66 as the accepted standard.

The mean value \( \mu \) is the expected mean of the process. If the data sequence is devices’ characteristic properties and expected to be stable, \( \mu \) is expected to be a constant. To monitor the change of this kind of properties, \( \mu \) is normally the average value of all the values received.

The standard deviation, or sometimes called moving range average, \( \sigma \) is normally unknown. It can be given a standard value or calculated by the average standard deviation function. In our implementation, the average standard deviation function is used and the moving range average is calculated by the formula below:

\[
\sigma = \frac{\sum |\text{value}(i) - \text{value}(i-1)|}{(n - 1)}
\]

with \( n \) is the number of data points received, \( \text{value}(i) \) is the current value and \( \text{value}(i-1) \) is the previous value received.
2.3.2. Other Shewhart chart methods

In the scope of this thesis project, we only need a basic and simple form of Shewhart control chart which is showed above to implement an alternative “drifting fault detection” module for comparison with CUSUM V-Mask method. There are also other Shewhart charts which are used in practice and they can be studied further as the future work:

- Shewhart X-bar and S Control Charts. Detail can be found in [9]
- Shewhart X-bar and R Control Charts. Detail can be found in [9]
- Shewhart R Control Charts [9]
3. ADVANCED DIAGNOSTICS AND PROGNOSTICS TESTBED (ADAPT)

3.1. General description

Advanced Diagnostics and Prognostics testbed (ADAPT) is developed by NASA Ames Research Center. The main aim for developing this system is to be used as a platform for experimenting and comparing the results of different diagnostics technologies and tools. It has been used as the platform for several competitions such as the first and the second international diagnostic competition held by PHM society. ADAPT depicts a Power system for a NASA’s space exploration vehicle and the lab where the system located is at NASA Ames Research Center.

ADAPT helps as an experiment platform for different diagnostic algorithm and strategy. The idea for diagnostic and prognostics assessment and comparison is that, during system runtime, different types of fault are injected causing the change in devices’ characteristic property, i.e. value of voltage, current, resistor, etc. The change could be abrupt persistent, drift (incipient), abrupt intermittent, etc. These changes are monitored by a system of sensor located in the system. This data is provided to the diagnostic system and this system with its diagnostic algorithm should detect the fault in the shortest time with the highest accuracy.

The testbed is the model of the electrical power system (EPS) of an aerospace vehicle. The EPS consists of a set of equipments which are used to generate and distribute power in the space vehicle. A set of sensors are used to monitor the system equipments parameters so the control can be changed according to the change of these parameters. Loads on EPS are made by consuming equipment which is a part of the aerospace vehicle. The values monitored by sensors are transmitted to the ADAPT network via the data acquisition subsystem using I/O equipments. These data is then redirected to the Diagnosis system (also called Test Article) where it is examined to detect faults. There are different types of Test Article. The typical Test Article triggers an alarm to the user whenever it detects a fault and the user will take action basing on the received information. Autonomous Test Articles can be programmed to take action by themselves by interact directly to the system without any manual intervention from users. Antagonist, which is another component of ADAPT, simulates faults in the EPS system by modifying the value of sensors or performs other imitated fault behavior of the system. It can be sending defective commands or turning off devices in the system. There are also other helpful components in ADAPT system such as Observer, which records all the information of the experiments, and Logger, which records data communicated among components in the system and stores in database.

The system under assessment in this case is not the EPS in testbed itself, but the Diagnosis System which is used to monitored it. The user uses the Antagonist to
simulate different types of fault to see how the Diagnosis System identifies faults and give the appropriate recovering actions.

3.2. System detail

Figure 3.1: ADAPT lab at Ames Research Center. Taken from [10]

Figure 3.1 shows a corner of ADAPT lab. The EPS supplies AC (Alternative Current) and DC (Direct Current) to the all parts which consume power in the space exploration vehicle. The hardware of the testbed is divided into 3 parts: Power Generation, Power Storage and Power Distribution. These components and how they connect to each other are depicted in Figure 3.2.
The power generation part lies in the first rack, consists of 1 solar panel and 2 battery chargers. These equipments connect to the power storage part, which has 3 batteries located on the second rack. Those batteries supply the power distribution part with 2 load banks.

3.2.1. Power generation unit

As it is clearly showed in Figure 3.2, the power generation has 3 sources: 2 battery chargers and 1 solar panel. Since the solar panel is placed in door, there are 2 halide lamps used to provide light energy for it. The chargers are connected to the wall sockets. These 3 sources are interchangeable and are connected to 3 batteries on rack 2. A relay system is used to make sure 1 charge does not connect to more than one battery at the same time, or prevent 2 chargers from connecting to each other.

The solar panel unit has a 100W solar panel. There is also a light transducer to monitor the light and a sensor to measure the temperature.

3.2.2. Power storage unit

The power storage unit consists of 3 sets of batteries, which are used to store the power delivered from the power generation unit, and a relay system. This unit is divided into 2 parts:
- Battery cabinet: The 3 battery sets are located in a cabinet. In each battery, there are 2 batteries of 12 volt connected serially with each other. 2 battery sets are 100 amp-hrs and the other one is 50 amp-hrs.
- Battery-load selection panel: this panel, which consists of relays to connect between load device and battery, connect from rack 1 (the power generation unit) and to rack 3 (the power distribution unit). The relay system makes sure that there is a 1:1 relation between load and battery, a battery does not connect to more than 1 load device, and vice versa. It is placed in the equipment racks.

3.2.3. Power distribution unit

The relay system in battery-load selection panel is used to redirect the power to the loads from the power storage unit. The power is routed to the power distribution unit, where there are 2 load banks which are identical to each other. An inverter is used in this unit to make use of the DC power received, converting from 24V DC from the battery to 120V AC. Circuit breakers are used to protect the load from being overloaded, then prevent the system from damaging when the current provided is out of control.

3.2.4. Control and monitor

Beside the 3 units above, ADAPT has a sensors system. It uses “National Instrument’s LabView software and Compact FieldPoint hardware” to get the data measured by the sensors and send the commands to the system. Different values such as voltages, temperatures, AC frequencies, current can be monitored by this hardware system.

In the implementation part, a diagnostic module will be built to monitor and detect faults in the hardware of this EPS, particularly the devices located in Power storage unit and Power distribution unit. Detail will be given in chapter 4.

To sum up, ADAPT system is built to be the environment for diagnosis experiment. It can be considered as the problem domain containing a set of runtime injected faults where different diagnostic systems with different algorithms can be used to solve the problem by detecting faults and might be giving solutions. ADAPT has been used in many diagnostic competitions. In the next chapter, we will build one module of a diagnostic system and run it against ADAPT as the experiment environment. The data used for testing is taken from the Second Diagnostics Competition DX-10.
4. IMPLEMENTATION

To apply the theories above in practice, a program is built as the preliminary data filter module of the diagnosis system performing on a part of ADAPT called ADAPT-Lite. It consists of 1 battery in the battery cabinet from the power storage unit connecting to a load bank in the power distribution unit through an inverter. Particularly, it consists of a battery, a number of circuit breakers, 1 inverter and different types of load: DC resistor, AC resistor and fan. Figure 4.1 depicts ADAPT-Lite, or Diagnostic problem 1 given by DX Competition.

![Figure 4.1: ADAPT-Lite – Diagnostic Problem 1 from [13]](image)

In the Second Diagnostics Competition DX-10, a “Diagnostic problem 2” is also given. This case covers the whole power storage unit with 3 batteries and the power distribution unit with 2 load banks (Figure 4.2). However, the data, which is the values monitored by sensors given by DX Competition, contains drifting fault is only in Diagnostic Problem 1 – ADAPT-Lite, so we will focus on ADAPT-Lite in the scope of this project.
Figure 4. 2: ADAPT – Diagnostic Problem 2 from [13]


4.1. Fault types in DXC’10 industrial track

Different types of fault are injected into the system. In our project, we focus on detecting drift fault in ADAPT-Lite diagnostic problem. Other types of fault types will also be briefly described, however the implementation to detect them will be done by other modules in the diagnostic system, which can be considered as future work after this thesis project. Figure 4.3 shows different types of fault existing in ADAPT-Lite and ADAPT taken from DXC’10.

<table>
<thead>
<tr>
<th>Aspect</th>
<th>Diagnostic Problem I</th>
<th>Diagnostic Problem II</th>
</tr>
</thead>
<tbody>
<tr>
<td>System</td>
<td>ADAPT-Lite</td>
<td>ADAPT</td>
</tr>
<tr>
<td>Fault Types</td>
<td>Abrupt Persistent</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Drift (Incipient)</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Abrupt Intermittent</td>
<td>No</td>
</tr>
<tr>
<td>Multiple Faults</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Figure 4.3: Fault types in DXC’10, taken from [13]

4.1.1. Drift

Drift fault occurs when the value gradually deviate from the correct value. In ADAPT-Lite, this type of fault is injected by a linear ramp as the formula below:

\[ P_f(t) = P_n(t) + m (t - t_{inj}) \]

- \( m \) is a constant
- \( t_{inj} \) is the fault injected time.

Figure 4.4 illustrate the how drift fault happens intuitively.

Figure 4.4: Drift fault profile, taken from [13]
4.1.2. Other fault types

- Abrupt persistent: Abrupt persistent occurs when there is a step change, not gradually deviation, in a value of a component. More detail about this fault type can be found in [13]

- Abrupt intermittent: this type of fault occurs when abrupt persistent fault occurs and disappear, and then occurs again several times. Detail about it can be found in [13]

4.2. Early drift fault detection application

In this project, the model is built and calculated in a java application. In case of ADAPT-Lite, we can see that the sensors monitor the current and the voltage. Particularly, these are the values of IT281, IT267, E281, ISH236, E240, E265, IT240, E242. Beside those values which are directly measured by the sensors, the value of resistors can be measured indirectly via the formulas below according to Ohm:

\[
\text{value of AC483} = \frac{\text{value of E265}}{\text{value of IT267}}
\]

\[
\text{value of DC485} = \frac{\text{value of E281}}{\text{value of IT281}}
\]

Basing on this fact, in our model we can construct 2 types of device: resistor and sensor. Resistor can be considered a sub class of Sensor since it has all the attributes and methods of Sensor, but the value is calculated by the values taken from a voltage sensor and a current sensor.

Each devices (sensors and resistors) in ADAPT-Lite are constructed with the value of \( h = 8 \) (standard value of \( h \)) and \( k \) chosen depending on how the particular value changes. On other words, \( k \) depends on how sensitive the device is. (Detail about \( h \) and \( k \), refer to 2.2.3 CUSUM-chart V-Mask method).
5. EXPERIMENT RESULTS AND CONCLUSION

5.1. Experiment results

The input for ADAPT-Lite system in DXC’10 can be found in [13]. The result of the application using CUSUM is showed in the following table.

Parameters: \( h = 8, k = 0.025 - 0.03 \)

<table>
<thead>
<tr>
<th>File Name</th>
<th>Devices</th>
<th>First detected fault time (s)</th>
<th>Fault injected time</th>
</tr>
</thead>
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<tr>
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<td>Experiment</td>
<td>Model</td>
<td>Parameters</td>
<td>Value</td>
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</table>
Take the case of IT267 for comparison between CUSUM method and Shewhart method. Figure 5.1 depicts the average value of component IT267 in a Shewhart chart. The CUSUM chart of the same case is shown in figure 5.2. Moving range control limit in the Shewhart chart and V-mask in the CUSUM chart is set to reasonable values by adjusting arguments so the drift fault can be detected in the shortest time and false alarm can be avoided.
Figure 5.1: Shewhart chart for drifting component IT267

Figure 5.2: CUSUM chart for drifting component IT267
5.2. Conclusion

The result showed that both methods can predict drift faults before the data actually exceeds the thresholds, but CUSUM chart is more effective than Shewhart chart in this particular experiment since drifting is detected much earlier. This result can also be seen in figure 5.1 and figure 5.2, in which the change of CUSUM value is significantly stronger than that of the average value in Shewhart chart. Shewhart charts are more intuitive, but less sensitive compared to CUSUM charts in detecting small data changes. This conclusion gave the answer for the Research question 2, CUSUM is the most suitable method to be used for detecting drift fault in the shortest time with reasonable accuracy particularly for NASA’s ADAPT system.
REFERENCES


3. David Tam, *A theoretical analysis of Cumulative Sum Slope (CUSUM-Slope) Statistic for detecting signal onset (begin) and offset (end) trends from background noise level*. The Open Statistics and Probability Journal, 2009, 1, 43-51


13. Second International Diagnostic Competition (DXC’10), Industrial Track Diagnostic Problem Descriptions. URL: [http://www.phmsociety.org/competition/dxc/10](http://www.phmsociety.org/competition/dxc/10), visited 02 November 2011