# Anytime Diagnosis Using Model-Based Methods for Satellite Diagnostics

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#### Abstract

Many satellite anomalies manifest themselves slowly over time and go undetected until they reach critical and possibly unrecoverable status. Because modern satellite systems are relatively reliable, the ground controller must perform the almost impossible task of attending carefully over long periods of time to telemetry readouts which almost always indicate nominal operation, while maintaining a constant readiness for the onset of failure. Humans are notoriously poor at that type of task. On the other hand, intelligent systems have been successfully used to monitor emerging trends in data streams and have been used successfully for tireless monitoring of manufacturing processes, changes in structure configurations, and deterministic failure patterns.

The problem then becomes to develop an "intelligent" real-time system for fault detection, diagnosis, and recovery/resolution of anomalies in satellite telemetry streams. This Model Based Reasoning Diagnostic Engine (MBRDE) is aimed at the combination of adaptive and knowledge-based intelligent methodologies that provides a satellite diagnostic assistant for incorporation into future satellite ground stations.

We present a framework for a diagnostic methodology that combines characteristics of model-based reasoning with those of anytime algorithms. We illustrate a bottomup modeling method that constructs a hierarchical device model, and a top-down traversal method that constructs a tree of potential component diagnoses for a given anomaly in the device's observed outputs. These methods combine to form an innovative framework for providing diagnostic assistance based on model-based principles given any amount of processing time.

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# Introduction

From their inception, intelligent systems have been applied to the task of automated diagnosis. Diagnostic expert systems were among the first successes of artificial intelligence, and played a key role in the development of the field.

As the devices under diagnosis grew more complex, diagnostic system programmers could no longer be assured

their *a priori* knowledge of how the devices might fail would be complete. It became apparent that expert systems' brittleness -- in the case of diagnosis, their inability to diagnose novel faults -- would limit their usefulness. In order to diagnose these unpredicted (or "unknown") faults, a more generalized diagnostic approach was needed. This need led to the application of the *model-based reasoning* paradigm to the task of automated device diagnosis.

The complexity of the diagnostic task has increased in ways beyond the number of components and interconnections in devices under diagnosis. Intelligent systems are called upon to provide diagnoses in applications where time is an increasingly critical resource, ranging from nuclear plant control to satellite health and status monitoring. In such real-time applications where operators must be notified of detected anomalies and their probable cause(s) in a timely manner, model-based diagnostic systems are faced with a tradeoff between diagnostic speed and detail. Simply put, the more accurate and detailed the device model, the more time will be required to reach a diagnostic conclusion.

Noting the similarity between this diagnostic tradeoff and that with which real-time planning systems must contend, we have looked to *anytime algorithms* for inspiration. This led to the development of a model-based diagnostic framework that allows a diagnostic system to produce a diagnostic response at any time, with the response becoming increasingly accurate as more processing time is allocated to the diagnostic task.

In satellite health and status monitoring, early notification is of great importance. Ground station operators must be apprised as early as possible of satellite health problems. In such a setting, it is more desirable to notify the operator of a telemetry anomaly and provide continuous feedback as the automated diagnostic system helps to narrow down the cause of the anomaly than to wait until a complete diagnosis has been formulated to provide any diagnostic assistance.

### **Model-Based Diagnosis**

While rule-based reasoning and set covering algorithms can provide quick and accurate diagnoses of complex

systems, they are limited to known failures and generally cannot respond to unknown conditions. This limitation greatly reduces their capability in the area of satellite diagnosis where the systems cannot be brought back into the lab for repair.

Model-based reasoning systems use a technique which base their diagnoses on knowledge of the actual system models and behaviors. This technique allows for the diagnoses of problems which were unanticipated when the system was developed. Since as many as fifty percent of on-board failures are unforeseen, providing the monitoring agents with the capability to determine the failed components is critical to the operation of these satellites[1].

However, model-based systems typically do not provide anytime diagnoses, since traversing an entire complex model will require large amounts of compute time. What this paper will present is a system for model-based reasoning that allows for the anytime diagnosis of satellite malfunctions.

# **Anytime Algorithms**

Anytime algorithms were originally implemented to solve the problem of the limitation of knowledge-based systems with time consuming algorithms and variable performance[2]. Anytime algorithms show an increasing quality of results gradually as computation time increases. This provides a tradeoff between resource consumption and output quality[3]. The quality of the diagnosis is defined by the depth of the analysis or the certainty. Each of these methods of obtaining quality may be developed in several different ways. For example, as an anytime algorithm progresses it may analyze the system in greater and greater detail. It may drop deeper down into the system hierarchy as computational time increases, providing diagnoses in varying steps. Another method to obtain this faster diagnosis is to use simpler behavioral models for calculating results at each component of the total algorithm. The algorithm would then use more complex behavioral models as more compute time is provided.

Anytime algorithms are normally defined in two different methods, interruptible and a defined computational time[3]. The interruptible method provides a more up to the second diagnosis, however it is much more difficult to implement. In this case we decided to develop an anytime algorithm using the defined computational time with a hierarchical interface. Thisallows us to provide for an interruptible style for a fast, less accurate diagnosis and a more accurate diagnosis as compute time is made available.

# **Anytime Diagnosis**

Our diagnostic framework can be characterized by its use of (1) *bottom-up modeling* resulting in the creation of a hierarchical model of complex devices under diagnosis and (2) *top-down traversal* of the model resulting in the continuous refinement of diagnoses generated.

# **Bottom-Up Hierarchical Modeling**

Our approach to device modeling emphasizes *abstraction* of the device's components to create a hierarchical model of the device under diagnosis. This model permits diagnoses to be produced at multiple levels of detail.

**Modeling Primitives.** Borrowing from graph theory, the basic primitives from which our models are constructed are *components* and *interconnections*. In addition, we have added a *telemetry* primitive to denote observable outputs generated by the device under diagnosis.

**Initial Representation.** Using these primitives, a device is first modeled at its lowest level of abstraction, or its greatest amount of detail. After the components and interconnections are established, the telemetry points are added which connect observable outputs to their origins in the device.

**Telemetry Origins.** The interconnections from which telemetry values originate are noted and entered into the device's database. These interconnections will be used to build, and also to prune, the *diagnostic tree* that is created as the device model is traversed. Once the interconnections have been recorded, the telemetry values are associated with the source components of those interconnections.

**Abstraction.** Once the low-level representation has been established, repeated groupings of components into successively-larger super-components create models of the device at higher levels of abstraction.

**Telemetry Tracing.** As groups of components are replaced by single components at higher levels in the hierarchical model, telemetry locations are passed up the hierarchy. The end result is that for each telemetry value, a list is established of its source component at every level of the hierarchical model.

## Example, Pt. 1

This bottom-up modeling process is illustrated in the following example. Figure1show the initial representation of a device. At its level of greatest detail, this device consists of twelve

Figure 1 show the initial representation of a device. At its level of greatest detail, this device consists of twelve (12) components, eighteen (18) interconnections, and five (5) telemetry points. From: Proceedings of the Twelfth International FLAIRS Conference. Copyright ' 1999, AAAI (www.aaai.org). All rights reserved.

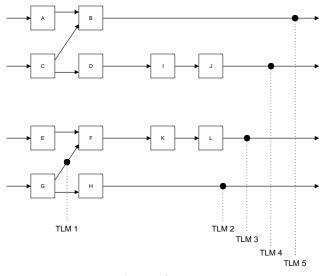
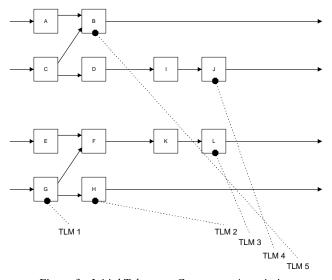


Figure 1: Initial Representation

Figure 2 lists the telemetry origins derived from the initial representations.

Figure 2: Telemetry Origins

Figure 3 shows the initial telemetry associations. These associations link the telemetry values with the components from which they are output.



*Figure 3: Initial Telemetry-Component Associations* Figure 4 enumerates the telemetry associations after the initial association step.

TLM1: G
TLM2: H
TLM3: L
TLM4: J
TLM5: B

Figure 4: Initial Telemetry Association Lists

Figure 5 shows the first grouping of the abstraction process. The components are grouped to create three (3) super-components consisting of four (4) sub-components each.

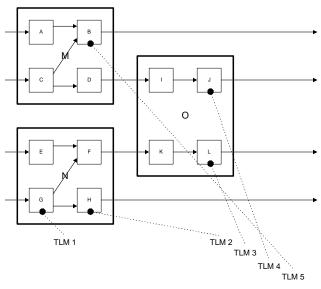


Figure 5: First Component Grouping

As the abstraction process proceeds, a component hierarchy is constructed in a bottom-up manner. The lowest level of this hierarchy is shown in Figure 6.

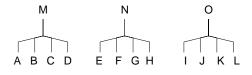


Figure 6: Initial Component Hierarchy

As this first grouping is made, the telemetry-component associations are propagated up the hierarchy, such that each telemetry value is now associated with its source component at this newly-created level of this hierarchy. This results of this propagation of associations is depicted in Figure 7.

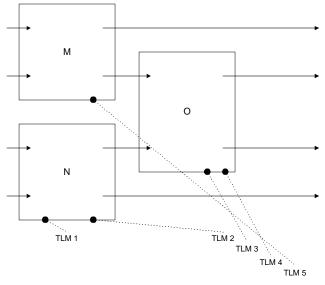


Figure 7: Second Telemetry-Component Associations

Figure 8 enumerates the resulting telemetry association lists as they are kept in the device's description database.

TLM1:	G, N
TLM2:	H, N
TLM3:	L, O
TLM4:	J, O
TLM5:	B, M

Figure 8: Updated Telemetry Association Lists

The first iteration through the bottom-up abstraction modeling sequence is now complete. This process ceases when a single-component level has been created as the top level in the device model, as shown in Figure 9.

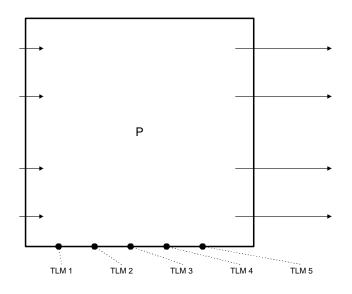


Figure 9: Final Representation

Figure 10 gives the final telemetry association lists, corresponding to the final top-level representation. Each telemetry value is now associated with its source component at each level in the model hierarchy.

TLM1: G, N, P
TLM2: H, N, P
TLM3: L, O, P
TLM4: J, O, P
TLM5: B, M, P

Figure 10: Final Telemetry Association Lists

Finally, Figure 11 depicts the final component hierarchy resulting from the bottom-up modeling process.

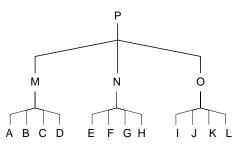


Figure 11: Final Component Hierarchy

## **Top-Down Diagnostic Refinement**

The second half of our anytime diagnostic framework consists of an algorithm for traversing the model with the goal of deriving a tree of components making up a list of potential diagnoses for any given telemetry anomaly. This model traversal algorithm provides an immediate highlevel list of possible components in which an error could lead to the telemetry anomaly in question, and also allows that list of components to be refined continually as time permits. Key elements of this process follow.

**Propagation.** The first step in deriving a tree of components that each represent potential diagnoses is to propagate a fault marker from the anomalous telemetry value back through the model. This propagation is repeated on a sub-component basis as the component tree is expanded.

**Replacement.** Components in the diagnostic tree are replaced with their set of sub-components.

**Expansion.** Sets of sub-components are expanded to form a more detailed diagnostic tree. The fault markers are propagated through the set of sub-components to determine their proper order in the diagnostic tree, which may result in the insertion of a branch into the tree.

**Disconnection.** As a set of sub-components is expanded, an existing branch in the diagnostic tree may no longer remain connected. As the more detailed propagation takes place, fault markers will not necessarily be passed to all paths of a branch. Those branches to which a marker is not passed will become disconnected from the diagnostic tree, and will therefore be removed from further consideration.

**Pruning.** The diagnostic tree is pruned using nominal telemetry observations. As fault markers are passed from component to component along their interconnections, the propagation ceases when an interconnection has been noted in the device database as the origin of a telemetry value and that value has been observed to be within its nominal operating range.

### Example, Pt. 2

This top-down process of building a tree of potential diagnoses is illustrated in the following example, which uses the device previously modeled.

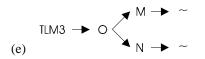
Given the observation of an anomaly at telemetry value TLM3 with all others OK, the initial propagation through the highest level of the hierarchy is shown in steps (a), (b), and (c). Note that "~" is used to denote a path termination.

- (a) TLM3
- (b) TLM3 → P
- (c) TLM3 → P → -

In step (d) component P is replaced with its subcomponent group (O,N,M).

(d) TLM3 → (O,N,M) → ~

In step (e) the fault marker is propagated through group (O,N,M). The group is expanded, and a branch is added to the diagnostic tree.



In step (f) component O is replaced with its subcomponent group (I,J,K,L).



In step (g) the fault marker is propagated through group (I,J,K,L). The group is expanded, and the diagnostic path connects to component N but <u>not</u> to component M.

(g) 
$$ILM3 \rightarrow L \rightarrow K \qquad N \rightarrow \sim$$

In step (h), component M and anything that follows it in the diagnostic path are disconnected, as they could not be the cause of a telemetry anomaly at TLM3.

(h) TLM3 
$$\rightarrow$$
 L  $\rightarrow$  K  $\rightarrow$  N  $\rightarrow$   $\sim$ 

In step (i) component N is replaced with its subcomponent group (E,F,G,H).

(i) TLM3  $\rightarrow$  L  $\rightarrow$  K  $\rightarrow$  (E,F,G,H)  $\rightarrow$  ~

In step (j) the fault marker is propagated through group (E,F,G,H). The group is expanded, and a branch is added to the diagnostic tree.

(j) 
$$ILM3 \rightarrow L \rightarrow K \rightarrow F \checkmark G \rightarrow \sim$$

Finally the path from component F to component is G is pruned from the diagnostic tree. Recall from our previous model-construction example that telemetry value TLM1 originates on the interconnection  $G \rightarrow F$  and has component G as its lowest-level source. Since TLM1 has been observed to be within its nominal operating range and no other anomalous telemetry observations have component G as their origin, fault marker propagation will not pass from F to G. The final diagnostic tree, consisting of components that are potential diagnoses for the observed anomaly at TLM3, is shown as step (k).

TLM3 
$$\rightarrow$$
 L  $\rightarrow$  K  $\rightarrow$  F  $\rightarrow$  E  $\rightarrow$   $\sim$ 

## Implementation

Originally, the intent of this system was to integrate a complete diagnosis system into a satellite ground station. However, because of constraints on the availability of the data interface, it was determined that using an in house system would be a more feasible option. In order to accomplish this task we decided to implement the diagnostic system a portable power supply on our Portable Physiological Monitoring System (PPMS). This system was originally developed for NASA for the physiological monitoring of astronauts in space. We believe that this represents the closest available substitute for an actual satellite system. Also a power supply demonstration using the PPMS could easily be reconfigured for a satellite power supply.

This implementation consists of 60 to 80 components, with 16 to 32 telemetry points read from the system. We use a PPMS as the telemetry measurement device as well the device under test. It provides up to 16 channels of A/D measurements from +/- 10 millivolts up to +/- 5 volts. The telemetry measurement PPMS taps into the power module of another unit at some chosen points and provides this data to the Data Collection and Analysis Environment (DCAE). This system then 'checks' the data and provides 'Good' or 'Bad' telemetry points into the MBRDE.

This system in itself is a simplistic expert system that provides the behavioral models for the system components. It provides the programmable capability to define system checks via an interactive function generator. Currently, this system can provides any system check that may be calculated via a RPN calculator interface. In this case, we are defining system checks as current and voltage bounds and behaviors. Simple examples include the limit checking of currents and voltages in certain states.

Obviously, this computation may have a strong effect upon the performance of the model-based anytime algorithm. However, there are qualifications for this expert system which provide fast, simplistic inputs to the modelbased algorithm without limiting its anytime performance or capability to provide diagnoses for unknown errors. The first point describes the simplistic component based model and the second describes the simple expert system.

The designers of satellite and other complex electronic systems have very accurate knowledge of the inputs and outputs of each component. This allows the designer to easily define a simple set of rules for the inputs and outputs of each component. This may also be a daunting task for a large complex system. The MBRDE system avoids this problem by allowing the designer to focus their efforts on upper subsystems and those lower subsystems which are particularly crucial and still provide a reasonable level of diagnosis. This method allows the designer to develop his own level of focus on the components and have the MBRDE system show faults in only higher subsystems or all the way down to the atomic component level.

The simple expert system model allows the designer of the model to quickly develop fault conditions without writing complex rules for each component. Since the MBRDE is only interested in the inputs and outputs of the individual components, the models for each component may be as simple as a limit check.

The MBRDE system is demonstrated by modifying the power module to produce known and unknown faults and use to MBRDE to identify the known faults and determine the best explanation of unknown faults, which we will then check. This system is easily portable for demonstration. Figure 12 is a diagram of the full MBRDE system.

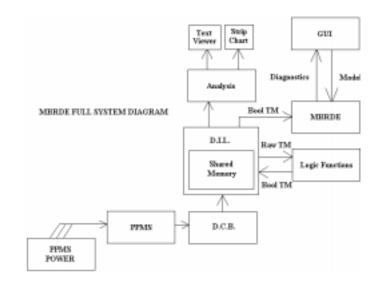


Figure 12 MBRDE System Diagram

The following steps trace the path through the diagram shown in Figure 12.

- Data taps on the PPMS Power supply send data to the monitoring PPMS.
- The monitoring PPMS unit collects the data from the power supply taps and sends it to Cybernet's Data Collection Broker (DCB).
- The DCB then converts the data into a stream format and stores this information in the Shared Memory of the Data Interface Library (DIL).
- The raw telemetry data is passed through logic functions in order to create boolean fault data.

- The boolean telemetry data is sent to the Model Based Reasoning Diagnostic Engine (MBRDE) which parses the data.
- The GUI sends the model to the MBRDE at any time during the process..
- Once the MBRDE has received both the model and data, it returns diagnostic information to be displayed by the GUI.
- The raw data can also be sent to the Analysis application from which it can be viewed by either a strip chart or text viewer.

The following figure displays the model representation of the PPMS power supply module.

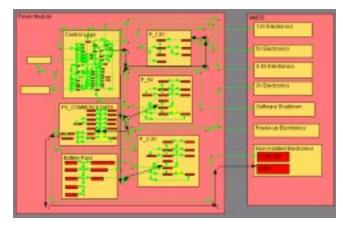


Figure 13 Depiction of the PPMS Power Supply Module

The early demonstration system used text-based model coding, which was somewhat arcane. To improve this, a JAVA-based model GUI was developed. This improved implementation also includes interfaces to the Common Object Request Broker Architecture (or CORBA) which provides an applications independent interface to the model based reasoning engine. This allows us to easily integrate the engine into other systems. The interface to the DCB is through this CORBA interface. The modelbased diagnostics User interface includes on-line help, model construction, and structured display features. This GUI allows the model developer to easily design the model graph for the system. The following figure show a simple model representation.

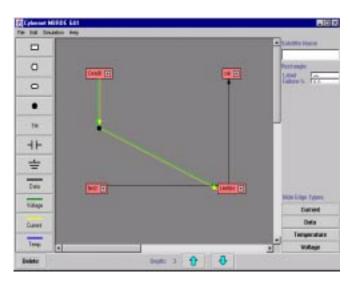


Figure 14 The Basic Java GUI Interface

## Discussion

We feel the innovation of the methodology presented here is the combination of model-based diagnostic methods with characteristics of anytime planing algorithms. Our diagnostic approach is able to produce a list of probable diagnoses immediately upon the recognition of an anomaly in the satellite's observed outputs. These diagnoses provide a list of possible failed components at a high level. From this point on, computational resources are devoted to elaborating that diagnostic tree to provide as much detail, or depth, as possible.

An important distinction between this and other work is that ours is focused on always having some diagnosis available for the operator. While the initial level(s) of diagnosis may at first seem somewhat less-than-useful, they do serve as general notice to the operator that something in the device has gone awry and can at least suggest a general area or set of areas in which the fault(s) might reside. This allows the monitoring agent to quickly react to satellite faults which may result in saving the system from complete loss.

# **Conclusions and Future Work**

This paper presents a significant portion of our work currently in progress. At this point we have developed a framework for performing model-based diagnosis that facilitates the derivation of a list of probable faulty components, and that derives this list in a continuous manner so as to always have at least some form of diagnosis available to the operator at any time. Using this framework as a foundation upon which to build, we are currently exploring the integration of finergrained diagnostic tools that will perform resolution functions given the list of potentially faulty components.

We also intend to pursue methods for easing the integration of device behaviors into our model. By developing simpler GUI interfaces for developing the behavioral models for each of the components a designer can quickly implement a diagnostic tool that will aid in development of the systems as well as the monitoring of the system. This will complement the existing structural descriptions and provide valuable information to aid in producing more accurate diagnoses.

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