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Research Paper

Design and Analysis of Diagnosis Systems Using Structural Methods

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Abstract

In sophisticated and automated technological processes, the consequences of a defect may rapidly spread, resulting in a decrease in process performance or, in the worst-case scenario, a catastrophic collapse. This implies that defects must be identified as soon as feasible, and choices must be taken to prevent their impacts from spreading and to limit process performance deterioration. Various defects influence the behaviour of the process in different ways, and the fault may be identified by ruling out faults for which the anticipated behaviour of the process differs from the actual behaviour. A model represents the anticipated behaviour of the process for various problems in model-based diagnostics.A diagnostic system is a gadget that detects problems. A variety of tests in the diagnostic systems discussed here use observations of the process to verify the consistency of various elements of the model. The collection of tests that is used to determine which problem has occurred must be carefully chosen. Furthermore, using fewer tests reduces the on-line computing cost of operating the diagnostic system and reduces the overall complex and time-consuming task of test creation.A two-step design process for building

diagnostic systems is presented, with the ability to choose which tests to employ implicitly by choosing which portions of the model should be tested with each test. The test design for each component may then be done using any current model-based diagnostic method.

There are two kinds of design objectives suggested in terms of the capacity to identify defects. The initial aim is to create a sound and comprehensive diagnostic system, which has the following properties. The diagnostic system calculates the flaws that, when combined with the observation, are compatible with the model. The intended isolability is the second objective, and it specifies which defects should be differentiated from other faults.

INTRODUCTION

Our contemporary civilization is heavily reliant on sophisticated technical processes that are dependable. Apart from meeting process performance criteria, human safety, environmental, and process protection standards are other examples of demands that must be met. All components of a process must operate properly according to their intended objectives in order to fulfil all of these criteria. A flaw is anything that alters the behaviour of a process component to the point that it no longer serves its intended function (Blanke et al., 2003). In complex and automated processes, the consequences of a defect may rapidly spread, resulting in process deterioration or, in the worst-case scenario, catastrophic collapse. As a result, defects must be identified as soon as feasible, and choices must be taken to prevent process failure by halting the spread of their effects and minimising process performance deterioration. It is not enough to know that a problem has happened; it is also essential to know what kind of fault has occurred in order to make the best choices. Problem detection is the process of determining whether or not a fault has occurred, whereas defect isolation is the process of determining the kind and location of the fault.

Methods for identifying and isolating defects are included in the area of diagnostics, and a device for this purpose is known as a diagnosis system. Figure 1.1 depicts the basic configuration of a diagnostic application, with a diagnosis system diagnosing a process. The process, that is, the system to be diagnosed, is considered to be operating in one of a number of pre-defined modes, referred to as system behavioural modes. A no-fault mode and certain fault modes are usually included in the collection of pre-defined system behavioural modes. An observation is the input to the diagnostic system that contains all available information about the current behaviour of the process. Sensor measurements and controller outputs are usually included in an observation. The goal of a diagnostic system is to identify and isolate process flaws based on observations.

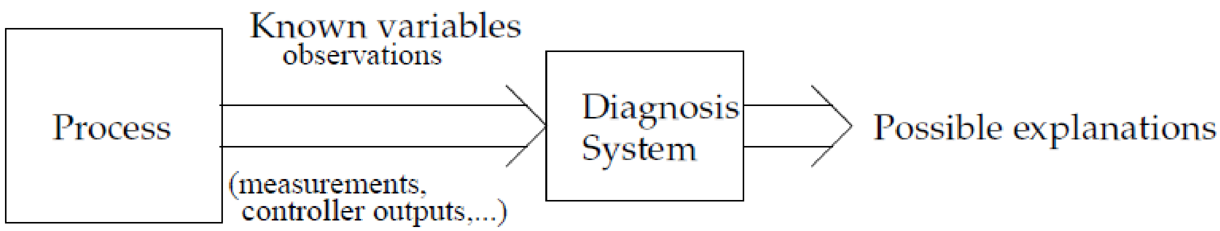

Figure 1.1: A general setup of a diagnosis application with a diagnosis system diagnosing a process.

There are two major drawbacks to evaluating each behavioural model individually. The first drawback is that the number of behavioural modes may be considerable, particularly when several faults are included, resulting in a high number of tests. The second drawback is that each system behavioural mode defines the behaviour of all process components, which implies that each test must take into account a model of the whole system, including all sensor and controller inputs. As a result, the computational cost of performing these tests is anticipated to be considerable.

Both of these drawbacks may be overcome by testing behavioural models that are subsets of equations. As a result, each test simply utilises the observed behaviour of a portion of the process, using just a few sensor and controller signals as inputs. Furthermore, by evaluating a tiny portion of a process, this single test covers all system behavioural modes that define the same anticipated behaviour for this section. As a result, by evaluating tiny subsets of equations, both the computing cost of each test and the number of tests may be decreased.

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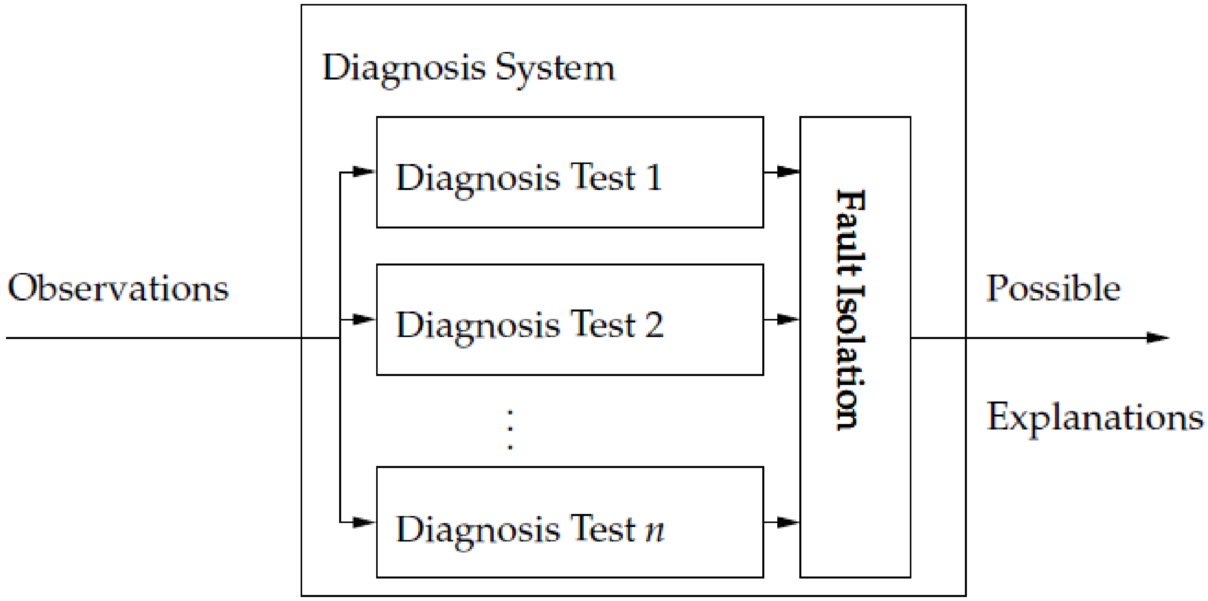

Figure 1.2: Architecture of a diagnosis system.

Good Fault Isolation Capability

There is a trade-off between low on-line computing complexity and excellent fault separation capabilities when developing a diagnostic system. We'll suppose that a diagnostic system designer sets a fault isolability objective, and that the on-line computational complexity is then reduced based on that goal. The designer may describe the fault isolation objective in this thesis by utilising one of the two different kinds of fault isolation goals listed below.

The initial objective is to build a diagnostic system that utilises all of this information, and a diagnosis model summarises all knowledge about the anticipated behaviours of the process. The best feasible diagnostic system is achieved by combining all information about the anticipated behaviours of the process. This kind of diagnostic system will be referred to as a sound and comprehensive diagnosis system.

The first objective is more difficult to achieve than the second. For complex systems, the first objective may be too ambitious, and it is therefore feasible to limit the first goal such that all anticipated behaviour information is only applied to a subset of behavioural modes. In addition, a simplified form of the second objective is to define the modes we want to differentiate from others.

A FRAMEWORK FOR MODEL BASED DIAGNOSIS

Fault diagnosis has been addressed in the literature primarily from two viewpoints. The first is control theory (here called FDI), for example (Gertler and Singer, 1990; Gertler, 1998), and the second is AI, for example (Gertler and Singer, 1990; Gertler, 1998) (Kleer et al., 1992; Reiter, 1987; Kleer and Williams, 1987; Hamscher et al., 1992). The literature on fault diagnosis in the area of control theory has mostly concentrated on the issue of residual generation. That is, how can off line generate residual signals that are zero in the fault-free situation yet sensitive to faults, given a system model. In the area of artificial intelligence, the emphasis has been on fault isolation and how to calculate residuals on the fly. In this chapter, we demonstrate how FDI and AI (or, more precisely, consistency-based diagnosis) techniques may be coupled to create a defect diagnostic framework that will be utilised in this thesis. The suggested framework is also based on statistical hypothesis testing concepts, namely the technique structured hypothesis tests from (Nyberg, 2002a, 1999).

We will be able to effectively handle fault models, many distinct fault kinds (e.g. parameter- and additive faults), and more than two behavioural modes by integrating these concepts from FDI, AI, and hypothesis testing.

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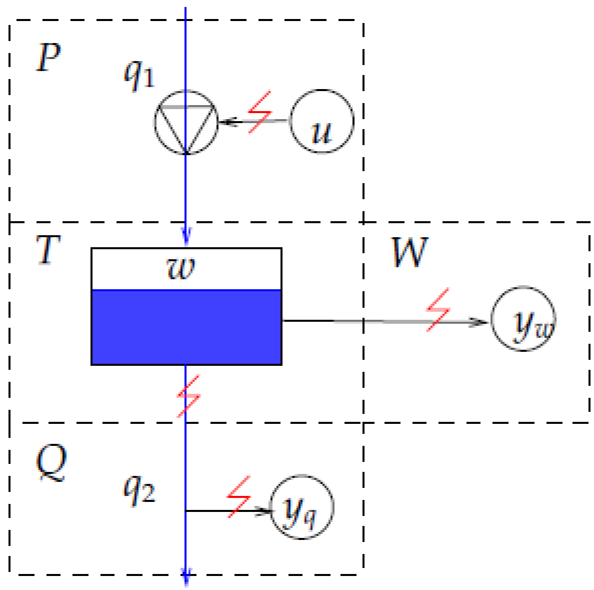

Figure 2.1: The system to be diagnosed. The location of possible faults are denoted with a red flash.

per component, general differential-algebraic models, noise, uncertainties, decoupling of disturbances, static and dynamic systems, and isolation of multiple faults.

The modeling framework and how information about different faults is incorporated in the model are described in Section 2.1. The design of a diagnosis system is then presented in Sections 2.2 and 2.3. The connection to FDI methods are more explicitly elaborated in Section 2.4. Finally, Section 2.5 discusses the output from the diagnosis system.

Modeling Framework

This section describes the modeling framework that is later used in the construc tion of the diagnosis system. Using this modeling framework, all information about the faults are included in the model. This fault information is then the basis for the reasoning about faults.

Throughout the chapter, we will exemplify some concepts and techniques on the following example.

Diagnosis Tests

A *diagnosis system* is assumed to consist of a set of *diagnosis tests* which is a special case of a general statistical *hypothesis test* (Casella and L.Berger, 1990) and a procedure to compute consistent behavioral modes by using the outcome of the tests. This idea has been

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described as *structured hypothesis tests* (Nyberg, 2002a). We will in this section discuss diagnosis tests and later, in Section 2.3, describe how several diagnosis tests are combined to form a diagnosis system.

To define a diagnosis test we need the notion of a *test quantity* $T_i(\mathbf{z})$ which is a function from the observations **z** to a scalar value. A *diagnosis test* for a noise free model can then be defined as follows:

Definition 2.2 (Diagnosis Test, δ_i)**.** *Let* $\Phi_i \subseteq \mathbf{B}$ *and let* sys *denote the system behavioral mode that the system to be diagnosed is in. A* ***diagnosis test*** δ_i*for the null hypothesis* H^0_i: sys $\in \Phi_i$*is a hypothesis test consisting of a test quantity* T_i: Z 7→ R *and a rejection region* $R_i \subset R$ *such that*

$$\text{sys} \in \Phi_i \rightarrow T_i(\mathbf{z}) < R_i \qquad (2.7)$$

The complement of the null hypothesis is called the alternative hypothesis and is denoted by H^1_i: sys $< \Phi_i$. Definition 2.2 means that if $T_i(\mathbf{z}) \in R^C_i$, sys $\in \Phi_i$ can not hold. This is the same thing as saying that the null hypothesis $H^0_i$is rejected and the alternative hypothesis $H^1_i$is accepted. The statement sys $\in \Phi_i$ becomes in this case a so called conflict (Kleer and Williams, 1987), i.e. an expression in behavioral modes that is in conflict with the observations.

Designing a Complete Diagnosis System

By computing the set of candidates as in (2.20) and following the two guidelines for designing tests, i.e. (2.15) and (2.16), the diagnosis system becomes complete as the next theorem shows.

Designing a Sound Diagnosis System

A diagnosis system is sound if and only if for each behavioral mode $b \in \mathbf{B}$ and for each observation

$$\mathbf{z} \in Z \setminus O(M_b) \qquad (2.32)$$

there exists a test δ_i such that the following expression holds

$$(T_i(\mathbf{z}) \in R_i) \wedge (b \in \Phi_i) \qquad (2.33)$$

Testing Small Models

In this section an example illustrates how the number of tests can be decreased by testing models with few equations.

Consider the electrical circuit shown in Figure 2.3 consisting of a battery *B*, two resistors *R*1 and *R*2, one ideal voltage sensor *S*1, and two ideal current sensors *S*2 and *S*3. All six component have two behavioral modes, the no-fault mode NF and the unknown fault mode UF. The set consisting of the no-fault behavioral mode, all single faults, and all multiple faults is **B**. The fault-free

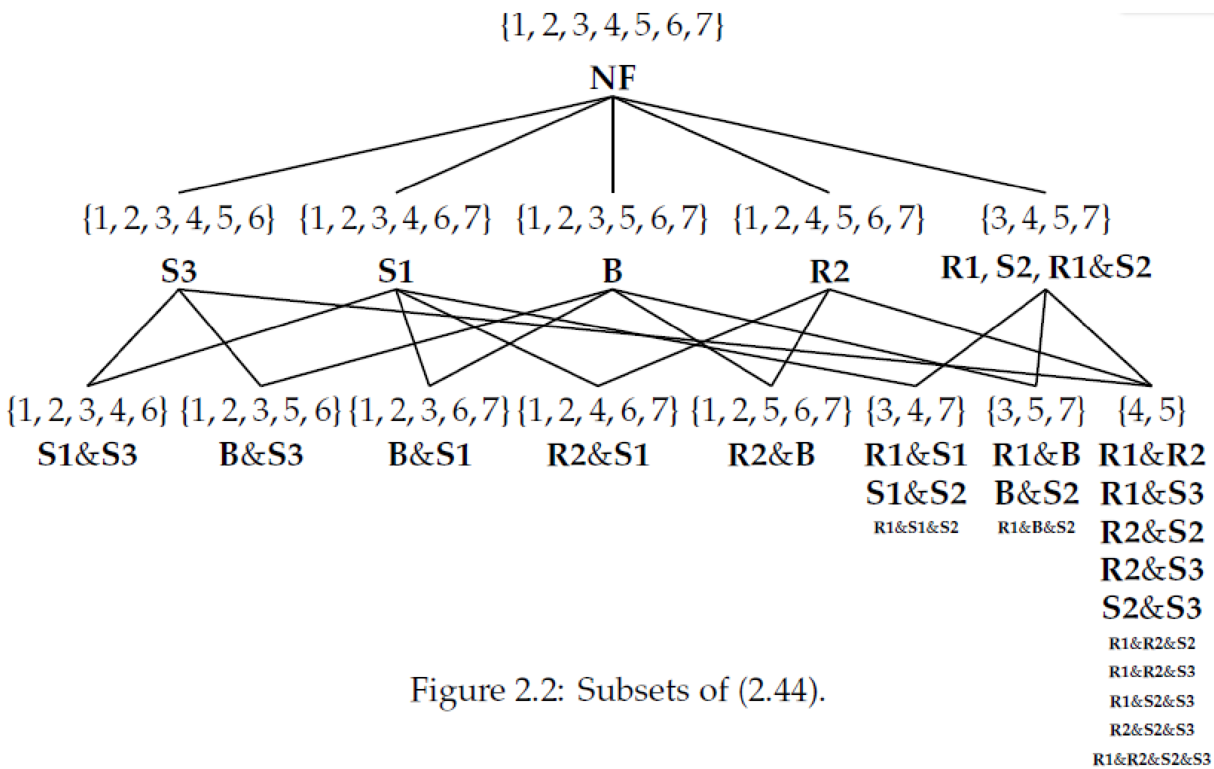

Figure 2.2: Subsets of (2.44).

behavior of the components are described by the model ***M***:

This means that

$$\mathbf{X} = \{I, I_1, I_2, V\}$$

$$\mathbf{Z} = \{U, y_V, y_{I2}\}$$

and the corresponding domains are X = IR^4 and Z = IR^3.

A straightforward way to fulfill (2.34) for all $b \in \mathbf{B}$ is as said before to test all behavioral models. For the electrical circuit, where all multiple faults are considered, there are $2^6 = 64$ behavioral modes. Next it will be discussed how to reduce the number of tests from the number of behavioral modes.

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First, there are behavioral models that are not rejectable models. In the electrical circuit only 29 out of the 64 behavioral models are rejectable models. The 29 behavioral modes with rejectable behavioral models are those seen in Figure 2.2. This figure will below be explained more in detail.

There can be several rejectable behavioral models with equal observation sets, i.e. O(M_1) = O(M_2) where M_1 and M_2 are two different behavioral models.

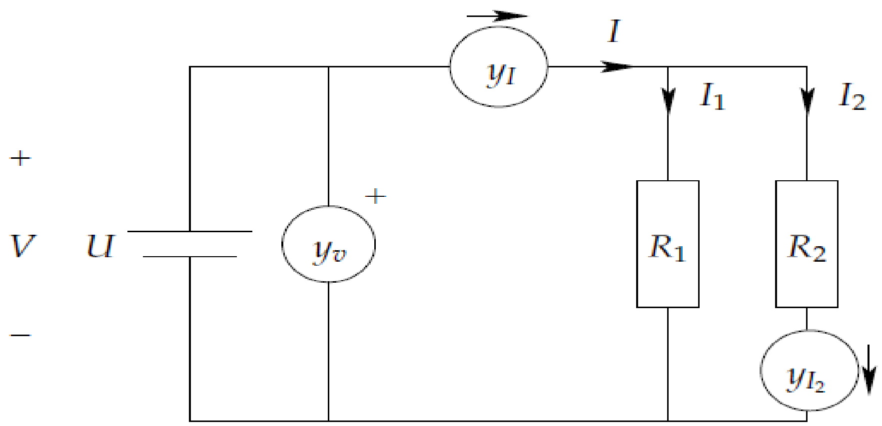

Figure 2.3: An electrical circuit

For the electrical circuit example the behavioral model {1, 4, 5, 6, 7} of **R1**&**R2** and behavioral model {1, 2, 3, 4, 5} of **S2**&**S3** have equal observation sets, i.e.

$$O(\{1, 4, 5, 6, 7\}) = O(\{1, 2, 3, 4, 5\}) = \{[U\ y_V\ y_I\ y_{I2}] | U - y_V = 0\} \quad (2.45)$$

A minimal set of equations with the same observation set is {4, 5} which is a subset of both the two behavioral models. It holds that

$$O(\{1, 4, 5, 6, 7\}) = O(\{1, 2, 3, 4, 5\}) = O(\{4, 5\})$$

Since the equation sets {4, 5}, {1, 4, 5, 6, 7}, and {1, 2, 3, 4, 5} have equal obser vation sets, it is sufficient to check the consistency of for example only {4, 5} to determine the consistency of both behavioral models. For each behavioral model in the example, it can be realized that there exists a unique minimal set with the same observation set. These equation sets and there corresponding behavioral modes are shown as a Hasse diagram in Figure 2.2 partial ordered by the subset relation. Instead of checking the consistency of all 29 rejectable behavioral models, it is sufficient to check the consistency of all the 14 models in the figure.

In the linear case it is also possible to determine the consistency of all models in the figure by checking the consistency of only the sets on the lowest levels. These 8 sets are the minimal sets that represents rejectable models. The constraint (2.34) for the behavioral modes on the lowest level imply that it is necessary to check all sets on the lowest level, except for {3, 4, 7}, {3, 5, 7}, and {4, 5} which can be replaced by {1, 3, 4, 7}, {1, 3, 5, 7}, and {1, 4, 5} correspondingly. Hence the minimum number of models that must be checked to obtain a sound and complete diagnosis system is 8. Hence this example shows that by testing small models the number of tests can be decreased.

Systems with Noise

The relation (2.7) can sometimes not hold strictly when the diagnosis test is used together with a noisy system. If noise is present, (2.7) can then be replaced by specifying the probability that (2.7) holds. In statistical hypothesis-testing theory, this requirement is usually written as

$$P(T_i(\mathbf{z}) \in R_i | \text{sys} \in \Phi_i) \leq \alpha \qquad (2.46)$$

That is, the probability of rejecting the null hypothesis H^0_i: sys ∈ Φ_i given that sys ∈ Φ_i holds must be less or equal to a significance level α called the false alarm probability. The idea behind hypothesis testing is to have a false alarm probability that is very small, in fact so small that it is realistic to assume that the formula (2.7) holds.

SOUNDNESS WHEN DIAGNOSING LINEAR STATIC SYSTEMS

Following the strategy described in Section 2.3.3, the construction of a diagnosis system starts with finding a set $\omega = \{M_1, . . . , M_n\}$ of rejectable models to test. If the diagnosis system should be sound, these models $M_i \in \omega$ must fulfill \

$$\mathcal{O}(M_b) = \bigcap_{M_i \subseteq M_b} \mathcal{O}(M_i) \qquad (3.1)$$

for all $b \in \mathbf{B}$ according to Theorem 2.2.

The model equations are considered to be linear static equations in this chapter. There are numerous solutions to (3.1) in general, but we're especially interested in rejectable sets with modest cardiacity, as discussed in Section 2.6. We construct rank-conditions to see whether a set satisfies (3.1). It is shown that checking the consistency of all minimum sets Mi Mb that are rejectable models is adequate under these circumstances. In the linear situation, such sets of equations are known as minimum overdetermined (MO) sets.

The primary challenge in this chapter is to choose a collection of models to test that satisfy (3.1) for all behavioural modes b B. This issue may be broken down into many sub-problems, one for each of B's behavioural modes. Only the sub-problem of identifying a given a behavioural model Mb is addressed in Sections 3.1-3.7. After you've solved these sub-problems, you may combine the answers to solve the complete issue for all behavioural modes in B, as shown in Sections 3.8 and 3.9.

Linear Static Models

Consider a linear static model M_b for a specific behavioral mode:

$$H_b\boldsymbol{x} + L_b\boldsymbol{z} = 0 \qquad (3.2)$$

where H_b and L_b are constant matrices, $\boldsymbol{x}$ is a vector of unknowns and $\boldsymbol{z}$ is a vector of known variables.

Example 3.1

Throughout this chapter we will use the electrical circuit example presented in Section 2.6 to illustrate concepts and theoretical results. Two behavioral modes **NF** and **R1**&**R2** and there corresponding behavioral models will be studied. By using the model (2.44), the behavioral

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model $M_{\mathbf{NF}}$ can be written in the matrix form (3.2)as

$$\overbrace{\begin{bmatrix} 0 & 1 & -1 & -1 \\ 1 & 0 & -R_1 & 0 \\ 1 & 0 & 0 & -R_2 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}}^{H} \begin{bmatrix} V \\ I \\ I_1 \\ I_2 \end{bmatrix} + \overbrace{\begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ -1 & 0 & 0 & 0 \\ 0 & -1 & 0 & 0 \\ 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & -1 \end{bmatrix}}^{L} \begin{bmatrix} U \\ y_V \\ y_I \\ y_{I_2} \end{bmatrix} = 0 \qquad (3.3)$$

The behavioral model for behavioral mode **R1&R2** is equal to the set $M_{\mathbf{R1\&R2}} = \{1, 4, 5, 6, 7\}$ of equations in (2.44).

To write for example the equations in $M_{\mathbf{R1\&R2}}$ in the form (3.2) by using the matrices H and L in (3.3), some matrix notation is needed. For a matrix A, an ordered *row index set R* and an ordered *column index set C* are defined such that $A = (A_{ij}|i \in R, j \in C)$, where A_{ij} is the (i, j)-entry of A. For $I \subseteq R$ and $J \subseteq C$, $A[I, J] = (A_{ij}|i \in I, j \in J)$ denotes the sub-matrix of A with row index set I and column index set J. Shorthand notations for the matrices $A[I,C]$ and $A[R, J]$ will be $A[I]$ and $A[:, J]$ respectively. Now, the set $M_{\mathbf{R1\&R2}}$ of equations can be written in the form (3.2) as where the matrices H and L are defined in (3.3).

$$H[M_{\mathbf{R1\&R2}}]\boldsymbol{x} + L[M_{\mathbf{R1\&R2}}]\boldsymbol{z} = 0 \qquad (3.4)$$

We will find sets ω of models M_i such that (3.1) is fulfilled for a behavioral mode b. That is the consistency of the models in ω will determine the consis tency of the behavioral models M_b. In (3.1) observation sets are used and in the next section we will discuss consistency and observation sets in the linear static case.

Observation Sets

For linear static models an observation $\boldsymbol{z}$ is assumed to be a snap-shot of the vector $\boldsymbol{z}$, i.e. a value of the vector $\boldsymbol{z} = \boldsymbol{z}_0 \in \mathrm{R}^{nz}$ where n_z is the dimension of $\boldsymbol{z}$. Let n_x be the dimension of $\boldsymbol{x}$. A linear model

$$H\mathbf{x} + L\mathbf{z} = 0 \quad (3.5)$$

consisting of the equations M is *consistent* with an observation $\mathbf{z} = \mathbf{z}_0$, if

$$\exists \mathbf{x} \in \mathrm{R}^{nx};\ H\mathbf{x} + L\mathbf{z}_0 = 0 \quad (3.6)$$

is true. The *observation set* O(M) for the equations M is then formally defined as $O(M) = \{\mathbf{z} \in \mathrm{R}^{nz} | \exists \mathbf{x} \in \mathrm{R}^{nx};\ H\mathbf{x} + L\mathbf{z} = 0\}$ (3.7)

The observation set O(M) can in the linear case be expressed without $\mathbf{x}$ as follows. Let N_H be any matrix such that the rows of N_H is a basis for the left null-space of the matrix H. This means that N_H has the maximum independent rows which solves

$$N_H H = 0 \quad (3.8)$$

By multiplying (3.5) from left with N_H, we get

$$N_H L\mathbf{z} = 0 \quad (3.9)$$

The expression (3.6) is equivalent to (3.9), i.e.

$$O(M) = \{\mathbf{z} \in \mathrm{R}^{nz} | N_H L\mathbf{z} = 0\} \quad (3.10)$$

This result will be shown analogously for linear differential equations in The orem 6.2. Each row of $N_H L$ defines a consistency relation, i.e. an equation containing only known variables. We will say that consistency relations are linearly independent if their corresponding rows in $N_H L$ are linearly indepen dent.

Redundancy and Rejectable Models

Existence of redundancy was defined in the previous chapter, and for linear systems, it is also possible to quantify redundancy as follows.

Conclusions

we demonstrated how to build a diagnostic system by starting with a diagnosis model and selecting a collection of rejectable models to test = M1,...,Mn. It was also shown there that a diagnostic system based on may be sound and complete if and only if the set (3.1) for all behavioural modes b B.

The theory and methods for obtaining a minimal cardinality solution of (3.1) given a diagnostic model M with linear static equations were provided in this chapter. One important conclusion is that if is selected as the set of all possible MO sets in the diagnostic model M, then for all behavioural modes b B, satisfies (3.1). It has also been shown that include all MO sets in to fulfil (3.1) for all behavioural modes b B is not always required. A theory for choosing MO sets has been established, including the rank condition as a crucial finding. The rank condition is then utilised to choose MO sets in Algorithm 2. The algorithm's output includes all minimum subsets that satisfy (3.1) for all behavioural modes b B. The set of all minimum sets is then reduced to a minimal cardinality set of MO sets. This is significant because a minimal cardinality set that meets (3.1) for all behavioural modes b B corresponds to a sound and comprehensive diagnostic system with the fewest tests. Several instances of reducing the number of tests in the development of reliable and comprehensive diagnostic systems.

Finally, the behavioural modes that affect any residual generated from M are provided by the equation assumptions according to (assump(M))C under a mild rank condition on the diagnostic model and given a MO set M. As a result, if the model's rank condition can be confirmed, no additional fault impact analysis of each residual is required.

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