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DIAGNOSTIC ANALYSIS FOR MECHANICAL SYSTEMS

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Abstract

An analysis and modeling method of the diagnostic characteristics of a mechanical or electromechanical system is presented. Diagnosability analysis is especially relevant given the complexities and functional interdependencies of modern-day systems, since improvements in diagnosability can lead to a reduction of a system's life-cycle costs. Failure and diagnostic analysis leads to system diagnosability modeling with the Failure Modes and Effects Analysis (FMEA) and component-indication relationship analysis. Methods are then developed for translating the diagnosability model into mathematical methods for computing metrics such as distinguishability and susceptibility. These methods involve the use of matrices to represent the failure and replacement characteristics of the system. Diagnosability metrics are extracted by matrix multiplication. These metrics are useful when comparing the diagnosability of proposed designs or predicting the life-cycle costs of fault isolation.

1 Introduction

1.1 The Diagnosability Problem

The complex electromechanical systems that compose modern-day machines are more efficient, cost-effective, reliable than those of only a few years ago. Many systems today are integrated in such a way that components have multiple functions and are managed by sophisticated computer control systems. While the benefits of this evolution in system architecture are numerous, such as increased reliability and simpler, more efficient designs, there is a significant drawback we seek to address in this research project. Because of the many component interdependencies in today's integrated systems, causes of failure are often difficult to distinguish. Thus, because of this increased complexity, more errors are made in the diagnosis and repair of electromechanical systems. This is a problem in *diagnosability*, the system characteristic defined as a measure of the ease of isolating faults in a system.

There are two approaches to alleviating problems with fault isolation. The first is to make improvements to the diagnostic process for systems already designed and in-service. This approach includes developing maintenance and diagnostic procedures and processes and incorporating electronic diagnostics into system design. There has been much research and application in this area of diagnosis. An example lies in the design of the Air Supply and Control System (ASCS) for the Boeing 767-400ER aircraft. Extensive built-in tests (BIT) were incorporated into the design to allow for problems to be easily diagnosed.

Less work has been focused on a second approach to the problem, improving inherent system diagnosability. This approach involves looking at the problem during the design stage and asking the questions: *How can this system be improved to make it easier to diagnose? What are ways of measuring this system's diagnosability during design?* In this approach we assume that changes in the structure of the system will affect the efficiency of diagnosing the system's failures. In endeavoring to understand and develop methodologies for improving diagnosability in this sense, we must have a good understanding of the diagnostic process.

Maintaining electromechanical systems is costly in both time and money, and diagnosability problems increase these costs. This fact is the primary motivation for exploring diagnosability improvement in systems ranging from airplanes to automobiles to high-tech manufacturing equipment. The ability to predict the diagnosability of a system early in its design stage would enable the building of systems with more efficient fault isolation, leading to reduced life-cycle costs.

1.2 Research Goals

The overlying goal of this research is developing a method for measuring system diagnosability, and thus allowing for the comparison of designs and the prediction of life-cycle costs of fault isolation. The methods should allow for designs with optimum diagnosability and minimized diagnostic costs.

In the course of pursuing this goal, we will outline in Section 2 the development of a diagnosability model, then demonstrate the use of Failure Modes and Effects Analysis (FMEA) and Fault Tree Analysis (FTA) as tools in the development of a diagnosability model. As an example, we will develop a model for an ice-maker system. Section 3 will present a new, more mathematically rigorous, method for computing diagnosability metrics. These metrics are important indicators in judging a system's diagnosability. We will continue the ice-maker example, validating the computation of the metrics. Concluding remarks are contained in Section 4.

The scope of the research will involve analyzing systems and their components to the level of the LRU (line replaceable unit). We will not concern ourselves with the inner structure of each LRU and what specifically has failed at that level of detail. (The terms *LRU* and *component* will be used interchangeably in this paper.)

1.3 Background Work in Diagnosability Analysis

Wong [1994] developed methods for minimizing both the time and cost of diagnosis early in the design stage. Wong developed a *checking order index* for each system component, which was calculated by dividing the probability of failure by the average time to check the component. A ranking order of components to be checked could then be established for each possible failure indication. Wong then developed an *expected time to diagnose* for a given indication.

Simpson and Sheppard [1994] devote a considerable portion of their book *System Test and Diagnosis* to diagnosability evaluation. They present a highly mathematical and theoretical analysis of diagnosis and testing adapted mainly for electrical and electronic applications. In evaluating diagnosability, they develop large matrices of test results and test conclusions to analyze and measure ambiguity and the ability to isolate faults.

Kurki [1995] researched model-based fault diagnosis, exploring the use of structural and behavioral models in examining fault detection and fault localization processes.

Ruff [1997] introduced the idea of mapping a system's *performance measurements* to system *parameters.* Performance measurements would be indications from lights, gauges, etc. Parameters were usually the system components being measured, such as valves, controllers, or actuators. The complexity of the interdependencies between measurements and parameters was directly related to the diagnosability of the system. Ruff also completed some initial work on evaluating competing designs based on life cycle costs associated with diagnosability.

Clark [1996] extended Ruff's work by establishing some valuable metrics based on performance measurement-parameter relationships. The most significant of these metrics, *Weighted Distinguishability (WD),* represents the complexities of interdependencies between components and indications. The distinguishability metric will be extended in this research, but evaluated from a different perspective.

Murphy [1997] developed prediction methods for a system's *Mean Time Between Unscheduled Removals (Unjustified)* ($MTBUR_{unj}$). The $MTBUR_{unj}$ metric is a significant component attribute in doing diagnosability analysis.

Finally, Fitzpatrick [1999] worked on developing methods for predicting *Mean Time Between Failures (MTBF)* and *Mean Time Between Maintenance Actions (MTBMA)* in addition to $MTBUR_{unj}$.

2 Diagnosability Modeling

The first step in evaluating a design for diagnosability is building a model, which shows the relationships between components of the system and possible failure indications. Sen, et al. [1996] state:

> …a common modeling paradigm is necessary to represent large systems consisting of electronic, electrical, mechanical and hydraulic subsystems… a test engineer analyses the system, either bottom-up or top-down, identifying various failure source-test dependencies of the system. The resulting model forms the basis for system-level testability analysis and fault diagnosis.

This section describes the system's Failure Modes and Effects Analysis (FMEA) and Fault Tree Analysis (FTA), and how they are used to build the diagnosability model. This model will then be used to calculate the system's diagnosability metrics.

2.1 Extracting Information for the Model

The main information sources for building the diagnosability model are the FMEA and the fault tree. These two documents contain different perspectives on the failure characteristics of a system, and together offer a complementary picture of a system's reliability and structure early in the design process. The FMEA is organized in a "bottom-up" approach [Leitch 1995], considering each of the system components and analyzing each possible failure mode for its effects at higher levels. The fault tree has the opposite perspective as a "top-down" analysis [Leitch 1995], and is organized by first considering possible failures and then analyzing all possible causes at lower structural levels. Taken together, the FMEA and fault tree can create a fairly accurate representation of the failure-structure relationships in a system needed for effective diagnosability analysis.[1]

[1] Family genealogy, which can be analyzed both bottom-up and top-down in "tree" diagrams, is a good analogy to FMEA and the fault tree. A bottom-up family tree will identify parents, grandparents, and great-grandparents, while a top-down family tree will identify brothers and sisters, aunts and uncles, and cousins. Together, like the FMEA and FTA, the two family models present a complete understanding of all family relationships.

2.1.1 FMEA

The FMEA is a widely used document for failure analysis, and will serve as our primary document for obtaining diagnosability information. From the FMEA designers can gain important insight into a system's structure and information flow early in the design process. The data and relationships in FMEA are also valuable input for predictive analysis such as criticality, operability, manufacturability, maintainability, and the diagnosability we are addressing here [Leitch 1995]. We will describe the basic structure of the FMEA document, as well as the enhancements needed for the FMEA to contain all of the relevant and necessary information for diagnosability analysis.

The FMEA is organized by components (LRUs), which are the smallest level of structure we identify for diagnosability analysis. For each of the components in the sub-system, assembly, etc. being considered, the basic FMEA provides the following information:

- The function of the components
- All of the most likely failure modes of the component
- The failure rates of each mode, or of each component combined with failure mode frequency.
- The failure effects on higher levels in the structure, from sub-assemblies to the whole system. [Leitch 1995]

For the FMEA to be most useful for diagnosability, each failure mode needs to have a description of its failure indications. Additionally, it may be helpful to have replacement time data for each component.

The diagnosability model can be constructed from the FMEA by making connections between components, failure modes, and indications as described in the FMEA table. This process will be outlined in section 2.2.

2.1.2 Fault Tree

Fault Tree Analysis may also be useful for building our model. Fault trees are widely used not only in reliability analysis, but also in safety analysis because they are able to predict causes of failure beyond mechanical malfunction [Bahr 1997]. For example, they are able to take into account human error and other external influences. And while FMEA allows designers to focus on specific components and their failure characteristics, fault trees tend to allow for focusing on a particular failure and the sets of component interactions which can lead to that failure. Thus, there is a new understanding of structural relationship uncovered by looking at the fault tree perspective. Furthermore, and important to diagnosability analysis, the fault tree is a valuable tool in computing failure rates. With knowledge of component failure rates, the fault tree allows the rates to be multiplied or added up the tree to obtain a cumulative failure rate for each failure.

The main disadvantage to the fault tree in building our diagnosability model is the binary nature of the events in the tree. Because we are interested in broadening our look at failure into a wider spectrum and more complete picture, we must be careful not to over-simplify based on the fault tree data [Harms-Ringdahl 1993]. Thus, it is best to use the fault tree as a supplementary data source to the FMEA.

2.2 Diagnosability Model

From the information in the FMEA we can analyze failure indications and establish unique indication sets. These indication sets are linked to system components to form our diagnosability model.

An indication is a measured or observed deviation from the desired behavior or performance of a system. The complexity in the diagnosis process arises because a given indication, or set of indications, does not necessary point to one failed component. The relationship between indications and components is illustrated in Table 1. Here, the lower case "i" represents an individual indication. The upper case "I" represents the set of individual indications which all occur for a given failure. Note that if we were including multiple failures in our model, we would add entries for multiple component failures (i.e., C2C3) along with their corresponding indications.

Component / Failure Mode	**Indications** ( ) = sometimes	**Indication Set**
C1 / FM1	i1	I1
C1 / FM2	i1, i2	I2
C2 / FM1	i1, i2	I2
C3 / FM1	i2, (i1)	I3, (I2)
C3 / FM2	i1	I1

Table 1 Simple Indication Set Illustration

In this simple case, when both i1 and i2 appear, there is ambiguity (thus forming an ambiguity group) because either component one or two has failed (or *both* have failed). Here, i1 and i2 form the unique indication set I2. The component-

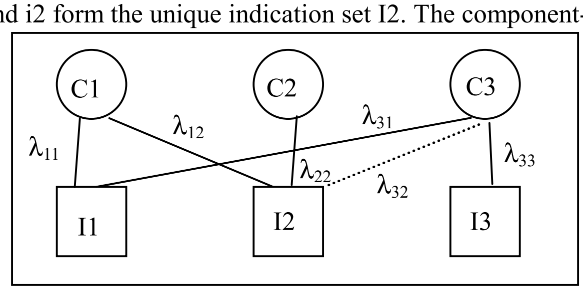

Figure 1 Component-Indication Diagram

indication diagram for this illustration is shown in Figure 1, and represents the critical information needed for our diagnosability model. Each line represents a unique failure mode. Attached to each mode is a particular failure rate λ.

Human error or time constraints could cause some indications to be missed. Additionally, certain maintenance procedures could affect diagnosis. For example, some airline procedures (or unofficial maintenance practices) allow for

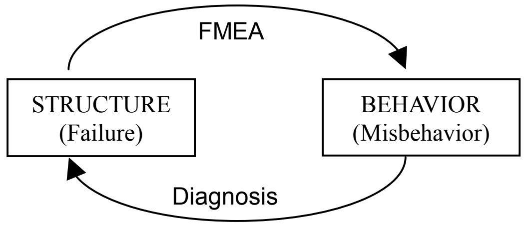

Figure 2 FMEA/Diagnosis Relationship [Eubanks 1996]

deferring a maintenance action or repeatedly replacing a part that is not likely failed but easily replaceable. Furthermore, human error is often the cause of misdiagnosis (drawing the wrong conclusions from correctly identified indications). These human factors and organizational factors will not be accounted for in our model, and in this paper we will assume that diagnosis is occurring with all indications accurately observed. However, metric values we calculate in the next section may be adjusted to account for these factors.

2.3 Validation Example: Ice-Maker

We will now use some of the modeling methods developed in this section to form a diagnosability model for a validation example.

Eubanks, Kmenta, and Ishii outlined the method for using an *Advanced FMEA* (AFMEA) for modeling a system's behavior. They suggested that their AFMEA could be used for diagnostics prediction [Kmenta 1998]. In fact, Eubanks et al. highlight the inherent relationship between FMEA and diagnosis early in their work. While FMEA builds a model of what behaviors result from given structures, the diagnosis process attempts to accomplish the opposite: seeking the system structure responsible for a given system behavior (or misbehavior) (Figure 2) [Eubanks 1996].

Eubanks, et al. [1996, 1997] use an icemaker to illustrate the AFMEA. In order to validate the suggested link between their AFMEA and diagnosis, we will extend the icemaker example by building its diagnosability model. Eubanks presents a function-structure mapping of the icemaker, but for diagnosability analysis we will need to expand this model to include failure indication and component failure rates.

Eubanks, et al. [1997] bring up an important diagnosability issue in the case of external factors. Often indications in a system are not caused by failure of one of the system's components, but rather due to some external influence. This cause could be an environmental factor (i.e., cold temperature) or from another sub-system interconnected with the one being analyzed. From a diagnosis perspective, this issue is significant because the failure indication may lead to the replacement of a part that is not failed.

The traditional FMEA only accounts for components of the system, not external factors. For the icemaker, Eubanks, et al. [1997] use their behavior modeling to identify the refrigerator's alignment as an external factor affecting the icemaker. External factors may also be extracted from a fault tree analysis. We will incorporate misalignment into our icemaker FMEA as an "external component."

Table 2 summarizes possible failure indications for the icemaker example. Notice that i5 and i7 are denoted "not observable." These indications are listed in a separate column of the FMEA, and will not be accounted for in forming indication sets. However, these indications would be helpful in a future analysis of diagnostic testing.

i1	No ice the bucket
i2	Ice overflowing
i3	Low ice level in the bucket
i4	Ice layer in bucket and/or fused ice cubes
i5	No water in the mold (*not observable*)
i6	Small or irregular ice cubes
i7	Ice stuck in the mold (*not observable*)
i8	Icemaker not running
i9	Feeler arm in the bucket
i10	Large or partially liquid ice cubes

Table 2 Failure indications for the icemaker

As we explained in section 2, there is a high degree of variation in failure modes, and therefore in component-indication relationships as well. The process of grouping indications into indication sets can be rather subjective, as was the case here. Table 3 describes the indication sets determined for the ice maker.

I1	No ice + ice layer
I2	No ice
I3	Ice overflow
I4	Low ice level
I5	Small ice size + ice layer
I6	No ice + feeler arm in bucket
I7	Small ice size

Table 3 Icemaker indication sets

Table 4 summarizes the likely component-indication relationships revealed in the FMEA.[2] The complete icemaker FMEA is presented at the end of the paper.

[2] Small variations of this model can easily be incorporated into the metric computations of section 3 to experiment with effects of changes in the model.

Component	Indication Sets
C1: Feeler Arm	I2 I6
C2: Switch Linkage	I2 I3 I4
C3: Switch	I2 I3
C4: Mold	I1 I5
C5: Freezer	I1 I2
C6: Water Delivery	I2 I5
C7: Mold Heater	I1 I2
C8: Ice Harvest	I1 I2
C9: Ice Timer	I2 I5
E: External Factors	I5 I7

Table 4 Component-Indication relationships for the icemaker

In the next section we will discuss the computation of diagnosability metrics. The icemaker example will then be continued in section 3.5 where its diagnosability metrics will be computed and discussed.

3 Distinguishability

The primary diagnosability metric is distinguishability (D), an estimate of the probability that a diagnostic technician, in the initial maintenance attempt, will correctly infer a specific component as the cause of failure, given some failure indication has occurred.[3] The metric comes in several forms: *indication, component*, and *system* distinguishability (D_{ind}, D_{LRU}, D_{sys}). The D metrics are all conditional probabilities of a justified removal.[4] The system metric is the sum of the indication or component metrics, each weighted by their respective failure probabilities. Table 5 summarizes the individual definitions.

Metric	Probability of (after initial maintenance action):
$D_{ind,\,i}$	justified removal, given *ith* failure indication
$D_{LRU,\,j}$	justified removal, given *jth* component failed
D_{sys}	justified removal, given *some* failure indication (or *some* component failed). Computed as: $\sum_{i=1}^{n} P_i \cdot D_{ind,i}$ or $\sum_{j=1}^{m} P_j \cdot D_{LRU,j}$ (where P is the probability of each indication or component failure)

Table 5 Definitions for Distinguishability metrics

Clark [1996] established a method for evaluating *system* distinguishability, which is important for comparing the overall diagnosability of competing designs. However, in order to evaluate the design of a system, it is helpful to have a metric that evaluates the distinguishability of each individual *component* in a given configuration. D_{LRU} fits this criteria by measuring the overall ability to separate a given component from others in the process of isolating faults. If the number of components mapped to a particular indication decreases, then D_{LRU} will decrease as well. While D_{ind} and D_{LRU} are very similar, the former helps in understanding ease of diagnosis and the latter is geared toward optimizing design.

3.1 Susceptibility

Another metric family related to D is susceptibility (S), defined as the probabilities of unjustified removals, and summarized in Table 6:

Metric	Probability of:
$S_{LRU,\,j}$	unjustified removal, given *jth* component removed
S_{sys}	unjustified removal, given *some* component removed. Computed as: $1 - D_{sys}$ or $\sum_{j=1}^{m} P_j \cdot S_{LRU,j}$

Table 6 Definitions for Susceptibility metrics

The main difference between S and D is that D is conditional on a particular *failure* occurring, while S is conditional on a particular *removal* occurring. When a particular component will never be replaced on an initial attempt, we will define its S value as 0. This is consistent with the conventions in probability theory.[5] Also note that S_{sys} is not unique information from D_{sys}, but merely the inverse probability.

3.2 Example problem: Distinguishability Analysis

To illustrate the method for obtaining these metrics, we will use a simple, abstract sample problem (not representing an actual system). From the FMEA (Table 7), we obtain the component-indication relationships for the system. The component-indication relationships from the FMEA are diagramed in Figure 3.

Component	Modes (Indication Sets)
C1	I1 I3 I5
C2	I3 I5
C3	I1 I4 I6
C4	I2
C5	I1 I2 I4 I5

Table 7 Abbreviated FMEA for example problem

[3]Note that this is a different definition of distinguishability from Clark [1996]. While it remains a similar system measure, this new D is specifically a probability of removal rather than an arbitrary index value.

[4] Removing a failed component is *justified.* Removing a working component is *unjustified.*

[5] Conditional probability of event A given that event B has occurred: $P(A|B) = P(A \cap B)/P(B)$. If $P(B)=0$, then $P(A|B)$ is defined as zero.

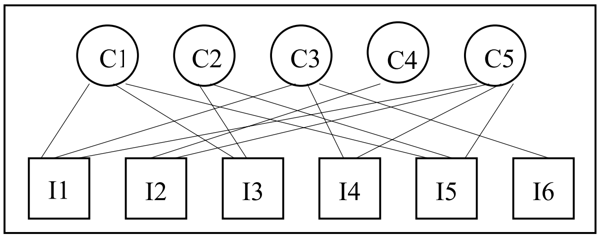

Figure 3 Component-Indication Diagram for example problem

As discussed in the last section, each failure mode (and correlated indication set) has a specific failure rate (λ). Failure rates are the expected frequency of failure over a long period of time. Over short periods, the frequency of failure will vary. These failure rates can be organized as shown in Table 8 for the example problem.

[10^{-4} failures/ hour]	C1	C2	C3	C4	C5	Ind. Rate	Ind. Prob
I1	2	0	4	0	3	9	0.085
I2	0	0	0	2	15	17	0.160
I3	3	2	0	0	0	5	0.047
I4	0	0	17	0	25	42	0.396
I5	10	12	0	0	3	25	0.236
I6	0	0	8	0	0	8	0.075
Comp Rate	15	14	29	2	46	106	
Comp Prob	0.142	0.132	0.274	0.019	0.434		

Table 8 Component-indication failure rate table for example problem

Each row can be summed to obtain an indication rate, $\lambda_{ind}(i)$. Each column can be summed to obtain a component's failure rate (for all failure modes), $\lambda_{LRU}(j)$. The sum of these rates is the system failure rate, λ_{sys}. The indication probability or component failure probability is computed by dividing the indication rate or component failure rate by the system failure rate.

3.3 The Failure Rate Matrix $\boldsymbol{\lambda}$ and Replacement Matrix R

For obtaining our metrics, we will convert the failure rate data into an $n \times m$ matrix, $\boldsymbol{\lambda}$ (There are n indication sets and m components). Additionally, we will form a $n \times m$ replacement matrix, **R**. The replacement matrix is an important mathematical representation of the predicted maintenance action for each indication. Each row of **R** contains a single 1 and the rest zeroes. The one is placed in the column representing the component that will be replaced for the corresponding indication. The replacement component can be determined using one of several criteria, including:

- Failure rate
- Replacement time
- Checking index (Failure rate / replacement time)

For this example, we will use the highest failure rate to determine the replacement component in each row of **R**. So for indication one, the "1" is placed in the third column because C3 has the highest failure rate. It is important to note that in this analysis we are considering only the *initial* maintenance attempt. Thus we have:

$$\boldsymbol{\lambda} = \begin{bmatrix} 2 & 0 & 4 & 0 & 3 \\ 0 & 0 & 0 & 2 & 15 \\ 3 & 2 & 0 & 0 & 0 \\ 0 & 0 & 17 & 0 & 25 \\ 10 & 12 & 0 & 0 & 3 \\ 0 & 0 & 8 & 0 & 0 \end{bmatrix} \qquad \mathbf{R} = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

3.4 Computing the Replacement Rate Matrix $\boldsymbol{\lambda}_\mathbf{R}$

From the $\boldsymbol{\lambda}$ and **R** matrices we obtain the $m \times m$ (square) replacement rate matrix, $\boldsymbol{\lambda}_\mathbf{R}$, by multiplying the transpose of the replacement matrix by the failure rate matrix (Equation 1). Equivalently, the element in the *ith* row and *jth* column of $\boldsymbol{\lambda}_\mathbf{R}$ is obtained by taking the dot product of the *ith* column vector of **R** with the *jth* column vector of $\boldsymbol{\lambda}$ (Equation 1a).

$$\boldsymbol{\lambda}_\mathbf{R} = \mathbf{R}^T \boldsymbol{\lambda} \tag{1}$$

$$\text{where } \lambda_{R_{i,j}} = \vec{R}_i \cdot \vec{\lambda}_j \tag{1a}$$

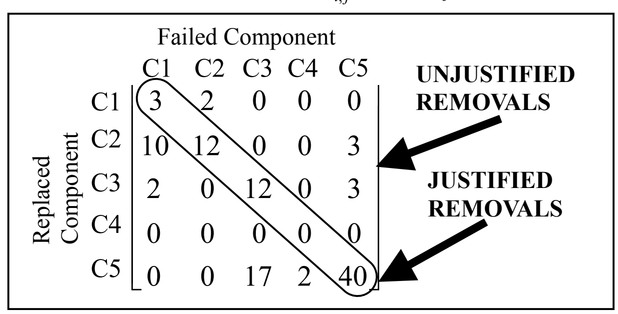

Figure 4 Replacement rate matrix $\boldsymbol{\lambda}_\mathbf{R}$

The $\boldsymbol{\lambda}_\mathbf{R}$ matrix shown in Figure 4 includes each combination of component failures and replacements. The numbers in the diagonal of the $\boldsymbol{\lambda}_\mathbf{R}$ matrix are the rates for justified removals. The numbers in the off-diagonals are thus unjustified removal rates. From these rates we can easily obtain all our metric values. For example, the failure rate for C1 is 15×10^{-4} failures/hour. The justified removal rate is 3×10^{-4}. Thus, D_{LRU} for C1 is computed as 3/15 = 0.200. Table 8 summarizes the metric values for this example problem:

I/C No.	D_{ind}	P_{ind}	D_{LRU}	P_{LRU}	S	P_{LRU}
1	0.444	0.085	0.200	0.142	0.400	0.142
2	0.882	0.160	0.857	0.132	0.520	0.132
3	0.600	0.047	0.414	0.274	0.294	0.274
4	0.595	0.396	0.000	0.019	0.000	0.019
5	0.480	0.236	0.870	0.434	0.322	0.434
6	1.000	0.075				
	D_{sys} =	**0.63**	D_{sys} =	**0.63**	S_{sys} =	**0.37**

Table 9 Metric Values for example problem

D_{sys} and S_{sys}[6] are a system-wide metrics, helpful in determining the system-wide effect of changes in diagnosability. In the current model, our system has a 63% probability of being diagnosed correctly after the observation phase of diagnosis. It is important to consider each metric value coupled with the respective failure probability. The probability value gives a sense of the importance of the indication or component metric in the perspective of the whole system. For example, indication three has a relatively low D_{ind} value of 0.600; however, its P_{ind} value of 0.047 suggests the indication's metric is not as significant (or likely) as others.

There are a couple of components that Table 8 highlight as good candidates for diagnosability improvement. We notice that component one has a low distinguishability of 0.200; however, this is less significant because its failure probability is relatively low. Component three is important to consider: it has only a 41% chance of being diagnosed correctly on the initial attempt, coupled with its significant failure probability of 0.274.

3.5 Validation Example Continued: Ice-Maker Diagnosability Metrics

Now that we have established the method for computing diagnosability metrics, we will use the information from the icemaker FMEA to calculate the metrics for the icemaker, listed in Tables 10 and 11.

Indication	D_{ind}	P_{ind}
I1 No ice + ice layer	0.693	0.121
I2 No ice	0.325	0.294
I3 Ice overflow	0.688	0.191
I4 Low ice level	1.000	0.084
I5 Small ice size + ice layer	0.417	0.129
I6 No ice + feeler arm in bucket	1.000	0.002
I7 Small ice size	1.000	0.179

Table 10 Indication metric values for the icemaker example

[6] The formulas for the system metrics are given at the start of section 3.

Component	D_{LRU}	S_{LRU}	P_{LRU}
C1 Feeler arm	0.667	0.000	0.004
C2 Switch linkage	1.000	0.454	0.311
C3 Switch	0.000	0.000	0.119
C4 Mold	0.000	0.000	0.011
C5 Freezer	0.000	0.000	0.036
C6 Water delivery system	0.643	0.583	0.084
C7 Mold heating system	0.778	0.307	0.108
C8 Ice harvesting system	0.000	0.000	0.036
C9 Ice timer	0.000	0.000	0.066
E External factors	0.789	0.000	0.227

Table 11 Component metric values for the icemaker example[7]

For the icemaker, the switch linkage and switch (C2 and C3) have interesting diagnosability characteristics. The switch linkage has a 1.00 distinguishability, weighed at a significant failure probability of 0.311 over the whole system, suggesting satisfactory component diagnosability. In contrast, the switch itself has a D_{LRU} of 0.0 and an overall 0.119 *misdiagnosis* probability,[8] the highest of all components.

The difference in C2 and C3 highlights the fact these components have high failure rates combined with the same indication profile. So for the best diagnosability, we want to configure systems so the components with lowest reliability have *different* failure indications.

The analysis also shows the water delivery system (C6) having the highest susceptibility for the icemaker, with S_{LRU} = 0.583. This high susceptibility is due to the water delivery system sharing indication set I5 with, among others, an external factors (E) failure mode. This observation serves to validate Eubanks' assertion that external factors are an important consideration in diagnostic and failure modeling [Eubanks 1997].

4 Summary and Conclusions

Our objective in this research was to create a method for modeling a system in way that readily describes the system's diagnosability characteristics, or the ease of isolating faults in the system. After presenting the problem of diagnosability and the motivations for pursuing improvement, we described the use of the FMEA and fault tree for extracting the information needed for developing a diagnosability model. We then presented a new process for computing diagnosability metrics by using matrix algebra to derive the highly informative replacement rate matrix $\boldsymbol{\lambda}_{\mathbf{R}}$. Important in this process was the new replacement matrix **R**, which described the predicted maintenance actions for given indications. From $\boldsymbol{\lambda}_{\mathbf{R}}$ we were able to extract many diagnosability measurements, including

[7] Notice that for C3, C4, C5, C8, and C9, both D and S are 0. This means these components will not be removed on an initial maintenance attempt.

[8] The misdiagnosis probability was not formally given a name as a metric, but can still be informative-as is the case here.

the distinguishability and susceptibility metrics. We successfully validated many of our methodologies with the icemaker mechanism presented by Eubanks [1997]. The new mathematics for computing the metrics are relatively simple compared to previous methods. Changes in the model can be input into a spreadsheet tool, instantly computing updated diagnosability measures.

The methodologies of this paper are generally applicable to many electromechanical systems. However, diagnosability analysis is most beneficial to systems with low reliability, high maintenance costs, and high complexity.[9] The results reveal important characteristics of the system, failure indications, and individual components for improving diagnosis times and minimizing the costs of fault isolation. Observing changes in the metrics disclose the diagnosability effects of design changes.

There is opportunity for future work in several areas. We could analyze failures further, taking into account the way a particular failure mode occurs. For example, is a component only partially failed, or failing intermittently? We could also more completely analyze the diagnostic process to include system testing. These characteristics would likely affect the nature of diagnosis and diagnosability analysis. Furthermore, the mathematical methods developed in section 3 could then be extended to account for system testing and calculating a testability metric, and used to predict a system's (or component's) Mean Time Between Unscheduled Removals (*MTBUR*). Thus, with further research, we could establish a broader understanding of failure, diagnosis, and measuring system diagnosability, and systems could then be evaluated more accurately for improved fault isolation.

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[9] While the icemaker example served as a simple case for validation in this paper, these criteria suggest it would not benefit as greatly from diagnosability analysis as other systems.

Icemaker FMEA Document

Component	Function	Failure Mode	Failure Rate [10^{-6} cycles]	Sys Effect (observable)	Indication Code ( ) = sometimes [Indication Set]
1. Feeler arm	Sense ice level in bucket	Broken off	3	No ice, feeler arm in bucket at times	1, (9) [2], (6)
2. Switch linkage	Feeler arm – Switch connection	Stuck closed	60	Ice overflow	2 [3]
		Stuck closed	50	Ice overflow	(2) [3]
		Stuck open	80	No ice	1 [2]
		Stuck open	70	Low ice in bucket at times	(3) [4]
3. Switch	Activate/deactivate ice maker	Stuck closed	50	Ice overflow	2 [3]
		Stuck open	50	No ice	1 [2]
4. Mold	Hold water, form ice geometry and size	Crack	8	Small ice, ice layer in bucket	6, (4) [5]
		Hole	1	No ice, ice layer in bucket	1, 4 [1]
5. Freezer	Freeze water	Not functioning	30	No ice, water in bucket at times	1, (4) [2], (1)
6. Water Delivery System	Fill mold w/ water	Not functioning	25	No ice	1 [2]
		Slow water	45	Small ice	6, (3) [5]
7. Mold heating system	Loosen ice	No heat	90	No ice	1, (4) [2], (1)
8. Ice harvesting system	Remove ice from mold	Not functioning	30	No ice	1, (4) [2], (1)
9. Ice timer	Allow proper freezing time	Not functioning	40	No ice	1 [2]
		Too fast	15	Small ice	6, (4) [5]
EXTERNAL: Refrigerator Alignment	Create a consistent water level in the ice mold	Small misalignment	150	Small ice	6 [7]
		Large misalignment	40	Small ice, ice layer in bucket	6, 4 [5]