D-matrix Based Fault Modeling for Cryogenic Loading Systems

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ABSTRACT

The study is motivated by NASA plans to develop technology for an autonomous cryogenic loading operation including online fault diagnostics as a part of Integrated Health Management system. For years, the diagnostic modeling effort is performed in many paradigms. None of these paradigms independently can provide a complete set of efficiency metrics: better diagnostics, lower run-time, etc. D-matrix, a causal 0-1 relationship between faults and tests, is proposed as a single representation between different model-based diagnostic methods for comparison and communication. This framework is suitable to create a common platform for communication via D-matrix for systems engineering process. The knowledge transfer between modeling techniques is done via D-matrix. In addition, D-matrix provides a common paradigm to compare the embedded knowledge and performance of heterogeneous diagnostic systems. D-matrix is generated from physics models to be used with faster run-time performance D-matrix based diagnostic algorithms. Additionally, we will also investigate if the derived D-matrix and thereby the physics model is sufficient and accurate for efficient diagnostics via iDME tool.

1. INTRODUCTION

Systems engineering is an important field to design and manage complex engineering systems during their life cycle. According to the NASA Systems Engineering Handbook, System Engineering is a robust approach to the design, development, test, evaluation and operation (DDTEO) of cyber-physical systems. In simple terms, the approach consists of identification and quantification of system goals, creation of alternative system design concepts, performance of design trades, selection and implementation of the best design, verification that the design is properly built and integrated, and post-implementation assessment of how well the system meets (or met) the goals (NASA Systems Engineering Handbook, 2007). In this paper, we will present integrated system health management (ISHM) techniques as a systems engineering process via a D-matrix framework. This common model can be migrated throughout the DDTEO process; thus enabling cost-effective system design to operations for NASA missions.

For systems engineering process, system health management is very critical during design, development, operation, and life cycle management of system components (Johnson, Gormley, Kessler, Mott, Patterson-Hine, Reichard, Karl & Scandura, 2011). This process is designed to improve system dependability while in operation. ISHM is a parallel capability across the entire system whose objective is to avoid failures where possible, but primarily reverts the system back to nominal functional behavior. Even though ISHM is very critical for system's operation, it is not fully accepted as an integral part in systems engineering process. This is partly due to the lack of a comprehensive framework that can well-define the requirements and knowledge in a simplistic way and can be easily interpreted by system engineers and health management community.

In ISHM process, system anomalous behavior is defined by low-level component failures. Fault diagnosis, specifically deals with detecting, isolating, and identifying the cause of failure. There are many fault diagnosis methods mainly categorized into model-based, data-driven, and knowledge-based. In this paper, we are defining a common representation for model-based methods via diagnostic matrix (D-matrix) (Luo, Tu, Pattipati, Qiao, & Chigusa, 2006). This is to give a global perspective for ISHM process in terms of the overall system. Traditional Hazard control lacks this global view to deal with cross-subsystem failure propagations.

D-matrix is a causal representation between faults and tests with 1 representing the relationship that the test can detect corresponding failure in the component and 0, otherwise. Our idea is to present D-matrix suitable to systems engineering process. This is performed in 2 ways. Firstly, D-matrix is defined as a communication platform between diagnostic modelers and system engineers. It is an ideal representation that can be easily understood by system engineers to approve or make changes with its closer to human reasoning. Secondly, it acts as a common conceptual diagnostic framework for knowledge transfer and compare among different diagnostic models. Importantly, it will help to analyze for the best diagnostic model representation. Additionally, any diagnostic model can be analyzed for errors using a tool called iDME via its representation as D-matrix. This is a simple effort compared to trying to analyze the original model itself for efficiency.

Diverse modeling techniques have different ways to interpret diagnosis. For years, the diagnostic modeling effort is performed in many paradigms. Fault trees (Vesely, 2002), failure modes and effects analysis (FMECA), graph-based dependency models (Deb, Pattipati, Raghavan, Shakeri & Shrestha, 1995) are some examples. None of these paradigms independently can provide a complete set of efficiency metrics: better diagnostics, lower run-time, etc. But, one thing that is common among all these techniques is the implicit knowledge of D-matrix. Not all techniques generate D-matrix for their diagnosis purpose. But, the information about fault-test dependencies can be easily established for any model via simulations or reachability analysis (Skiena, 2011) or interpretation of the model by an expert. This is why, as discussed earlier, D-matrix can serve as the common representation across models. To support this idea, in this paper, we will present the preliminary study to build D-matrix from closer to real system physics models operating at different system modes. Additionally, we will analyze the generated D-matrix via iDME tool for sensor optimization and diagnostic performance (Kodali, Robinson, & Patterson-Hine, 2013).

We will demonstrate deriving D-matrix for the cryogenic transmission line that includes pipes of different diameter, control and dump valves. The cryogenic transmission is a high-fidelity first-principles physics model. Thus, deriving D-matrix from this model would help to achieve run-time diagnostic performance and sensor optimization. The causal 0-1 relations between faults and responses of pressure and temperature sensors will be obtained empirically by simulations of a moving front homogeneous two-phase physics model of cryogenic chill down in transmission lines. There will be associated test logic to determine if the sensor measurements represent nominal (0) or any faulty condition (1). Specifically, the generated D-matrix contains more than one system mode; thus, the modeled faults have different signatures in different system mode. D-matrix always represents the system in a single system mode. Thus, multiple D-matrices are required, one for each system mode. But, in this paper, we built one aggregated D-matrix with each row corresponding to a failure mode and system mode. We will also investigate if the derived D-matrix is sufficient to obtain efficient diagnostics performance with the existing sensors. In this paper, we used the same simulated data for building and then validating the D-matrix. By doing so, we are training the model to correct answer. But, in our case, as we are analyzing only for observability, using the same data should be fine. Generally, it is advisable to have different datasets for both.

Thus, this paper presents the methodology to generate and analyze D-matrix from high-fidelity physics model of the cryogenic transmission line. This is our first step to define a unified systems engineering process across different modeling techniques. In Section 2, we will discuss D-matrix and iDME tool. In Section 3, we will describe the model for cryogenic transmission line. We will elaborate the contributions of this paper in Sections 4 and 5. The first contribution is to generate D-matrix from physics model of cryogenic system. This is done by simulating data from the physics model. Secondly, the generated D-matrix will be evaluated for diagnostic performance and sensitivity towards the defined test logic of each test. This is presented in Section 5. In this paper, we demonstrate that the current model is only partially observable and thus to improve efficiency, more tests need to be added. Tests need to be designed to disambiguate an ambiguous set of faults accordingly. This acts as guidance for the system designer. In Section 6, we will briefly discuss the innovation of this research. We will summarize the findings and present the future work in Section 7.

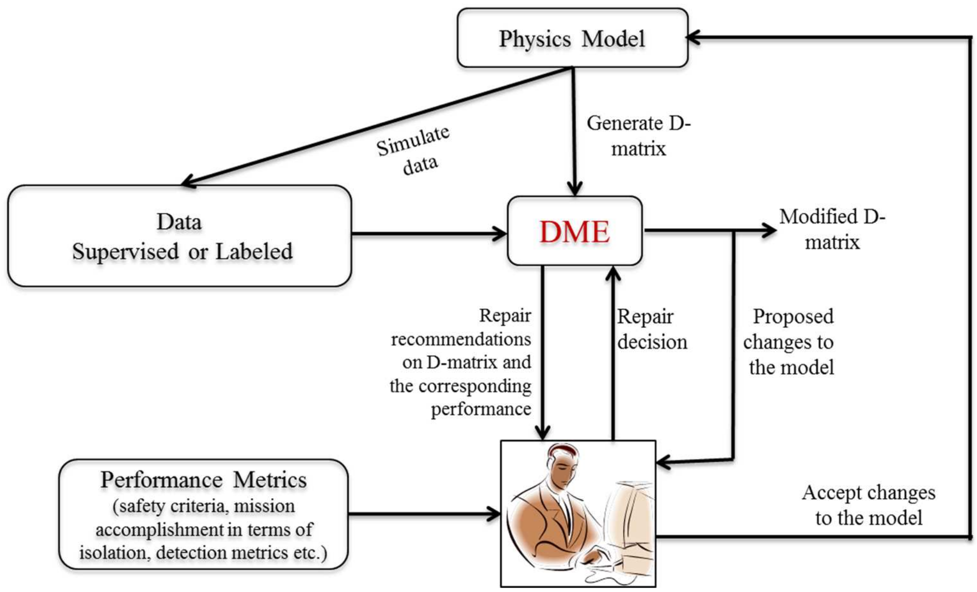

Figure 1. iDME architecture for physics model.

2. DIAGNOSTIC MATRIX (D-MATRIX) AND TESTABILITY ANALYSIS VIA IDME TOOL

Most dependency modeling techniques represent the system in the failure space. It is sufficient to model only the fault propagation to various monitoring points (tests). Thus, this type of dependency modeling captures only the minimum necessary information. This is contrary to the regular qualitative and quantitative techniques (Kuipets, 1993). They require complete specification of system components, the state and observed variables associated with each component, and the functional relationships among the state variables. Acquiring this precise information is not always possible with increasing complexity in systems. Even after modeling, it will be difficult to analyze these models for testability and diagnostic performance.

D-matrix provides the required simplistic view for our purpose that results in lesser footprint during real-time implementation and can be applied to large-scale systems with faster processing time. This matrix is also popularly known as dependency matrix, fault dictionary, or fault signature matrix. This matrix is obtained from directed graphs based on first principles via reachability analysis. Each test is analyzed to find the corresponding observed failure source (Deb, Pattipati, Raghavan, Shakeri & Shrestha, 1995). The dependency between a failure source and test is defined if the test can detect the fault when it occurs. This is identified as “1” in the D-matrix, otherwise it is “0”. These Boolean expressions can be conceived as test fail (1) or pass (0) in real sense. More than one test can detect a single failure source. Each test is identified by corresponding logic that determines if the test has failed or passed. The test logic can range from simple threshold checks to complicated signal processing techniques like Fourier transforms or statistical or trending tests. Dependency models include both D-matrix and test logic. The concept of D-matrix is popularized commercially by TEAMS software which employs multi signal modeling framework (Qualtech Systems Inc.).

The concept of D-matrix is quite popular in aerospace diagnostic community. Due to its widespread usage, it is standardized as “diagnostic inference model” (IEEE Std 1232-2002). Most diagnostic algorithms, for example Bayesian inference, case based reasoning, rule based inference, set partitioning can be applied easily for models based on D-matrix concept (Sheppard & Butcher, 2006).

2.1 iDME Tool: Analyze D-Matrix

The diagnostic information of the system is summarized by D-matrix. Hereafter, all diagnostic analysis is performed using this matrix. In other words, the original model is not required anymore unless the modeler wants to understand the trace back and modify the schematics. But in an another perspective, the major contribution of this paper is to utilize D-matrix to analyze efficacy of the corresponding physics model. In such case, the physics model is modified accordingly based on the findings from the D-matrix via iDME tool.

iDME tool, with the aid of supervised data (data is labeled with corresponding nominal or faulty state), debugs and proposes repair strategies to D-matrix by coordinating with the decision maker (user) (Kodali, Robinson, & Patterson-Hine, 2013).

iDME is defined as a combined process of computer and user decisive mechanisms where computer provides

Table 1. Tests list.

Test Name	Sensor	Test Name	Sensor
Tests 1&2	PT104	Tests 13&14	PT148
Tests 3&4	TT102	Tests 15&16	TT149
Tests 5&6	PT161	Tests 17&18	PT152
Tests 7&8	TT162	Tests 19&20	TT156
Tests 9&10	PT145	Tests 21&22	PT158
Tests 11&12	TT146	Tests 23&24	TT191

Table 2. Faults list.

Fault Name	Valve
Fault 1	CV120 stuck closed
Fault 2	CV117 stuck closed
Fault 3	CV117 stuck opened
Fault 4	CV112 stuck closed
Fault 5	CV112 stuck opened
Fault 6	Heat leak
Fault 7	Mass leak

platform of the diagnostic analysis of the system model with the aid of supervised data and the decision maker performs the role of accepting/declining repair strategies based on the analysis of performance metrics and technical expertise (see Figure 1). Five D-matrix repair strategies are identified arranged in ascending order of cost effectiveness. These strategies range from addressing duplicity in faults and tests, repairing the fault universe to accommodate lower/higher level fault modeling (re-define the level of fault modeling by adding or removing rows), repairing/changing the wrapper/test logic, repairing 0's and 1's in the D-matrix entries, and adding/removing tests. They are included in an iterative loop to experiment for better performance along with the decision maker. The performance criteria are based on fault detection and isolation metrics derived from the mission objectives by the user. Then, the decision maker accepts/declines the repair strategies based on before and after performance. More details of this framework can be found in (Kodali, Robinson, & Patterson-Hine, 2013).

The efficiency of the inference process is directly proportional to better coverage of the defined failures by tests and the separability between the rows of D-matrix (fault signatures) (Sheppard & Simpson, 1992). In this analysis, we will test for ambiguous, hidden, and masking faults (Kodali, Singh & Pattipati, 2013). Two failures are ambiguous if their fault signatures are similar i.e. the two corresponding rows are identical. The failures which are masked by a fault are its hidden failures, i.e., the fault signature of a hidden failure is the subset of the signature of the fault. A masking false failure occurs when the symptoms of two or more failures add up to mimic the failure of an unrelated element, i.e., the combination of their signatures produces the signature of another fault. The existence of these types of failures indicates partial coverage of the model. This reduced observability is due to increased failure definitions while the monitoring points are reduced. In such a case, the solution would be to add more tests to improve detectability of the failures. We will provide guidance about what tests need to be designed in terms of which fault they need to detect or isolate from other faults.

For the framework proposed in this paper, data is collected from high fidelity physics model (cryogenic) which is closer to reality. This is done by injecting faults and then collecting corresponding sensor data from the computer-aided simulation model. The simulated model is very close to reality as will be discussed in the next section. The same data is also used to build D-matrix.

3. DESCRIPTION OF CRYOGENIC SYSTEM

The fault diagnostics was applied to the chill down stage of cryogenic loading operation in the experimental cryogenic loading system that has been developed at the Kennedy Space Center to test autonomous regimes of operation (Johnson, Notardonato, Currin, & Orozco-Smith, 2012). The KSC cryogenic testbed system consists of a 6,000 gallon storage tank is connected to a 2,000-gallon vehicle tank with pipes of different diameters, control and dump valves, pump and sensors to measure pressure and temperature along the transfer line. The liquid motion through the transfer line is driven by an elevated pressure in the storage tank, which at working conditions is designed to suppress potential boiling of liquid cryogen at the operating temperature. During the initial stages of the loading operation, when the transfer line is still at high temperatures a substantial part of the incoming nitrogen boils increasing the pressure in the transfer line and slowing down the cryogen liquid motion. A set of control valves allows liquid flow in the corresponding segments of the pipe and dumping valves are to be opened sequentially to maintain the liquid flow and to allow for a gradual chill down of the system as the hot gas is substituted sequentially by the cold vapor, the two-phase mixture, and the cryogenic liquid.

A set of the valve open/close positions together with the dynamics of the storage tank pressure constitutes the filling protocol, which depends on the design of the experiment. A set of the temperature (TT102, TT162, TT146, TT149, TT156, TT191) and pressure (PT104, PT161, PT145, PT148, PT152, PT158) sensors allows for control of the

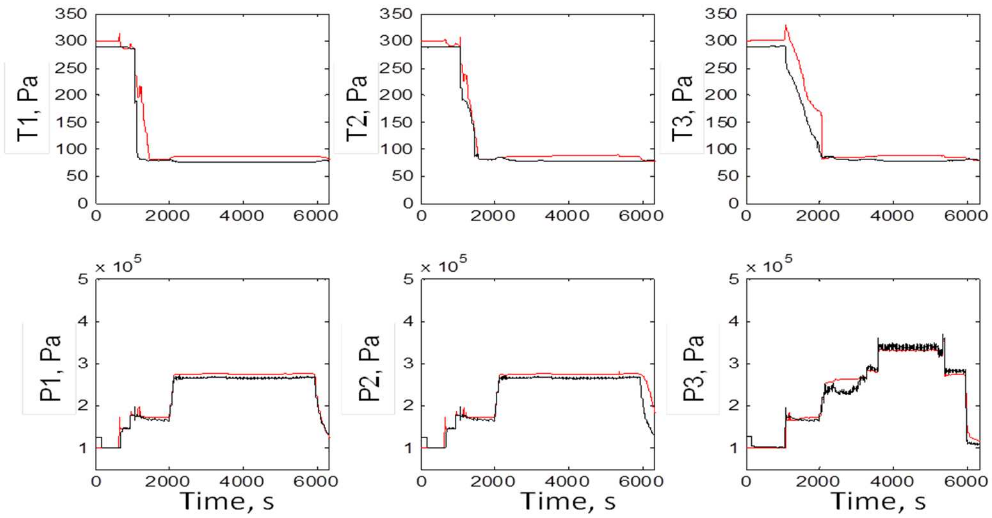

Figure 2. The predictions of the homogeneous model (red lines) are compared to the experimental data (black lines) for three pressure and three temperature sensors.

conditions of cryogen flow (Table 2). The faults in the valves, mass and heat leaks, clogging in the pipes could cause the pressure and temperature deviate from the nominal values (see Table 2).

The total length of the transfer line is about 45 m. The diameter of the stainless steel pipe varies along the pipeline from 0.1524 m to 0.0254 m. The thickness of its walls is approximately 3 mm. Initially, the storage tank is full and the vehicle tank is empty with the flow path between the tanks blocked. An ullage pressure in both tanks equal to the atmospheric pressure. Then the storage tank is pressurized first, and the chilldown begins. The dump valves CV112, CV117 and CV120 regulates the cryogenic flow and their positions for nominal regime are shown at Fig.2. In this study we consider the list of faults presented in the Table 2. The deviation from the sensors data over the margin values was used as tests. For each sensor we had two tests that represented deviation above the nominal value and below the nominal value (Table 1).

We use the homogeneous moving front model (Hafiychuk, Foygel, Ponizovskaya, Smelyanskiy, Watson, Brown, B & Goodrich, 2014) to simulate both the nominal and the fault regimes. The homogeneous model describes the properties of the two-phase flow in terms of the mixture density (ρ) and the mixture enthalpy (h)

$$\begin{aligned} &\rho = \alpha\rho_v + (1-\alpha)\rho_l; \\ &\rho h = \alpha\rho_v h_v + (1-\alpha)\rho_l h_l; \\ &h = x h_v + (1-x) h_l \end{aligned} \qquad (1)$$

here α is a void fraction, ρ_v and ρ_l is the density of the saturated vapor and liquid, h_v and h_l is the enthalpy of the saturated vapor and liquid, x is mass quality.

Assuming that phasic velocities for the gas and liquid are the same and equal to u, we can write the mass, momentum and energy conservation equation in the reduced form:

$$\begin{aligned} &\rho_{,t} + (\rho u)_{,z} = 0, \\ &(\rho u)_{,t} + (\rho u^2)_{,z} = -p_{,z} - \frac{1}{A}(\tau_w l_w)_{2\phi} - \rho g \sin\theta, \\ &(\rho e)_{,t} + (\rho u h)_{,z} = \frac{1}{A}\dot{q}_w l_w. \end{aligned} \qquad (2)$$

Here τ_w is the friction losses l_w is the pipe length, g – gravity, θ is the angle if the pipe, q_w is the heat transfer from the pipe walls to the mixture and A is the cross section area of the pipe.

All the interphase heat and mass transfer terms and interface friction terms cancel each other due to so-called jump conditions. The wall temperature (Tw) is determined by the reduced energy conservation equation in the form

$$c_w \rho_w A_w \frac{\partial T_w}{\partial t} = H_{fw} l (T - T_w) + H_{amb} l_o (T_{amb} - T_w) \qquad (3)$$

Here c_w is the specific heat for the pipe walls material, ρ_w is the density of the pipe walls material, A_w is the walls surface area, H_{fw} is the heat transfer coefficient from the walls to the mixture and H_{amb} is the heat transfer coefficient from the ambient to the walls.

Additional important simplification to speed up the calculations is to neglect inertia in the momentum equation, which reduces this equation to the following form

$$\left(\frac{1}{\rho}\frac{\dot{m}^2}{A^2}\left(\frac{x^2}{\alpha\rho_g}+\frac{(1-x)^2}{(1-\alpha)\rho_l}\right)\right)_{,z} = -p_{,z}-\left(f\frac{l}{A}+K\right)_{2\varphi}\frac{\dot{m}^2}{2A^2\rho}-\rho g\sin\theta, \tag{4}$$

where f and K are frictional losses and minor losses estimated at the center of the cell on the staggered grid. The solution of the equations (1)-(4) is achieved using a two step Adams-Moulton scheme (Hairer, Nørsett & Wanner, 1993), (Hafiychuk, Foygel, Ponizovskaya, Smelyanskiy, Watson, Brown, B & Goodrich, 2014). The set of equations for the mass and energy conservations (1st and 3rd equations in (2)) are solved to find new pressure and mass using of old velocities, then, new velocities are found by solving quasi-steady momenta equation (4).

The order of the steps may vary depending on the initial and boundary conditions. The solution of the energy conservation equation for the wall temperature is decoupled from the solution of the fluid equations and is performed in the end of each time step for both algorithms.

In the context of the model based fault diagnostics, it is important to ensure that models produce time accurate predictions for the cryogenic loading dynamics. For this purpose the model was verified and validated. The versions of the code developed for the cryogenic health management applications were tested using multiple flow conditions and verified by comparison of the model performance with the predictions of the baseline model of the cryogenic chilldown developed in SINDA/FLUINT (Kashani, Ponizhovskaya, Luchinsky, Smelyanskiy, Sass, Brown, & Patterson-Hine, 2014).

The model was validated on the KSC cryogenic testbed experimental data. The Figure 2 shows the comparison between the simulated data (red line) and the data from the corresponding pressure and temperature sensors (black line). The model accurately capture the main pressure and temperature transients observed during chill down of the cryogen transfer line.

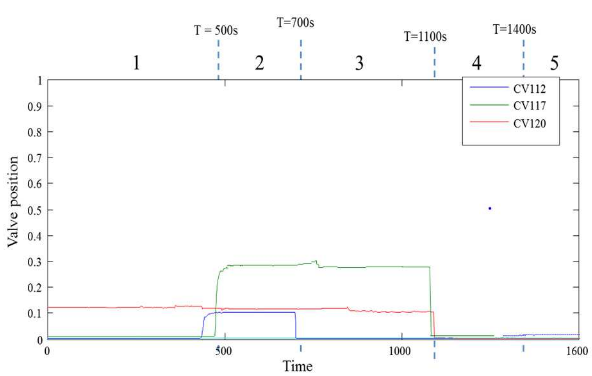

Figure 3. Valve positions.

4. GENERATE D-MATRIX FROM CRYOGENIC MODEL

For the demonstration purpose, we considered 7 faults and 24 tests (12 sensors) as shown in Tables 1&2. Failures correspond to valves. These valves can either stuck open or closed manifesting as failures in the system by affecting the liquid flow. Each sensor corresponds to two tests with maximum and minimum threshold limits, respectively.

Each failure mode has one corresponding supervised data file. Each file is simulated over 1600s from the computer-aided cryogenic simulation model. As the model is closer to real-time model, the simulations are as good as operational data (shown in Figure 2). The fault is injected at the start time of the file and is present throughout 1600s. Thus, there are 7 files in total. For this paper, we use these files to build D-matrix and then analyze for sensor optimization.

The cryogenic model operates at different system modes depending on the valve positions. The opening position of valves is shown in Figure 3. We find that the time plot is divided into 5 sections at 500, 700, 1100, 1400, and 1600 seconds. Each section determines a system mode. In D-matrix context, each failure is defined by the corresponding fault signature in terms of 0's and 1's for each test. But these failures behave differently with respect to test detectability depending on the system mode. They can have different fault signatures. Traditionally, in such a case, there are multiple D-matrices for each system mode. In this paper, we will construct a single aggregated D-matrix with each row corresponding to failure mode and system mode. That means, each failure mode has multiple representations with each system mode.

Another issue with the current model is that the sensor measurements are influenced by failures after a delay. This is the case with the temperature sensors because it takes some time for the temperatures to raise or drop due to failure. Generally, the knowledge about this delay is incorporated in the inference algorithm. But, as the current design analysis is off-line, we do not consider analyzing for these delays and use sampling for every 100s to offset the delay effect. We focus on the test design efficiency assuming that the delay is inevitable.

Here, we will enumerate the steps to generate D-matrix using the data simulated from the physics model.

1. Define the list of failure modes and tests. The failure modes are duplicated in each system mode.
2. Simulate data corresponding to each failure mode. At least one file is required for each failure mode.
3. Define test logic corresponding to each test. We employed simple threshold checks for each test. If the sensor measurement goes above or below 5% the simulated value, the corresponding test is failed.

4. Generate test outcomes (passed (0) or failed (1)) based on sensor measurements and test logic. This is done for all the supervised data files available.
5. As the tests are associated with delays to detect failures, the data is sampled at the rate of 100s. This is done to offset the delay effect. Thus, we have 16 time points in each data file for the data collected over 1600s.
6. Now, we start generating the fault-test relationship for each file sequentially. Ideally, after analyzing the data file for a fault, 5 fault signatures corresponding to each system mode are generated.
7. The D-matrix entry is 1 if the test fails at least once during the selected data points. That means, during the system mode, the test should at least fail once to be included as 1 in the entry for the corresponding fault and system mode.
8. The generated D-matrix for each failure mode in each system mode is listed in Appendix. Each failure mode is appended with underscore and the corresponding system mode number. But, for space convenience only the corresponding failure mode no. is appended with underscore and system mode no. The columns and rows with all zeros are removed.

5. ANALYSIS OF D-MATRIX WITH IDME TOOL

We started the analysis with the generated D-matrix via iDME Tool. In this paper, we aim at providing guidance to design extra tests to improve diagnosability. For this analysis, we did not consider to repair test logic. So, we analyze only D-matrix with the aid of simulated data. This analysis is very similar to the regular testability analysis, except for the fact that the data is used to validate the model. This will be helpful to assess the model's ability to withstand noise in sensor measurements. Simulations can be done with various noise levels and the resulting D-matrix can be analyzed for efficiency.

The generated D-matrix is partially observable; thus there are duplicate rows present. The duplicate failure modes are listed in Table 3. It is imperative that additional tests need to be developed to be able to isolate among duplicate faults (only when recovery action is different). There is no other way to differentiate among these faults. Similarly, there are duplicate (redundant) columns (see Table 4). They are left as they are because they can be useful for other set of failures not considered here.

As we can see that the faults corresponding to open and close functions of a valve are not duplicate, but their faulty behavior is similar to the faults in the open and close positions of other valves, respectively. During system mode 2, stuck close failures corresponding to cv112 and cv120 are duplicate. Similarly, during system modes 3, cv112, cv120, and cv117 stuck close have similar signatures. Faults 2, 4, 5, 6, and 7 are duplicative during system modes 4 and 5. These faults are only detected by TT191 sensor. This indicates that there should be additional tests to isolate among these faults. The new test can analyze the existing sensor TT191with new test logic or can be a new sensor. In a similar way, we can analyze other duplicate faults to design appropriate tests. Generally, duplicate faults are grouped if the recovery action is similar. But, this is not the case here.

Table 3. List of duplicate faults.

Failure Mode 1	Failure Mode 2	Failure Mode 1	Failure Mode 2
Fault1_2	Fault4_2	Fault1_5	Fault2_5
Fault1_3	Fault2_3		Fault4_5
	Fault4_3		Fault6_5
Fault1_4	Fault4_4		Fault7_4
	Fault6_4	Fault3_1	Fault5_1
Fault2_1	Fault4_1		Fault5_2
			Fault5_3
Fault3_2	Fault3_3	Fault3_4	Fault5_4

Table 4. List of duplicate tests.

Test Name	Test Name	Test Name	Test Name
PT104High	PT161High, PT145High	TT104Low	TT146Low
PT104Low	PT161Low	TT104Low	TT149Low
TT104Low	TT162Low	TT146High	TT149High

Table 5. List of hidden faults

Fault	Hidden faults	Fault	Hidden faults
Fault1_3	Fault1_2	Fault2_2	Fault1_2
	Fault1_4		Fault2_1
	Fault1_5	Fault3_2	Fault3_4
	Fault2_1		
	Fault2_4		
	Fault6_3		

Another important problem with partial observability is the existence of hidden and masking faults. This results in ambiguous groups during diagnosis. These groups are always hard to isolate without proper system design. This can be avoided by adding more tests. The list of hidden faults after grouping duplicate faults is given in Table 5. In this case, if the hidden fault is of the same failure mode but a different system mode, then there is no need to design a new test because the recovery action is similar. But, remember that there are duplicate faults for the faults listed in Table 5. So, by analyzing Tables 3 and 5 together, it is understood that the system failures in cv117, cv120, and cv112 are either duplicative or hidden during stuck open or close. But, another consideration we ignored in this paper is the delay after which the test fails for the corresponding failure. This could probably alleviate the ambiguity in the current model. This will be pursued in future research.

Thus, we need to carefully analyze the existing set of tests along with their logic and understand if it requires additional sensors or additional tests that analyze the existing sensors differently. In this paper, we will not include the follow-up strategy to find the placement for the additional required sensors.

6. INNOVATION

This research is en-route to establish a singular ISHM framework to communicate with systems engineering process. This research will result to provide a unified and simplistic view to ISHM process that can be easily interpreted by system engineers; thereby integrating it with systems engineering process. The proposed framework is neither a new method for better diagnostics nor a replacement to the existing model-based techniques, but is an integrated framework that works to better each of these models. This work can be viewed as a common platform that helps in evaluating design and reducing errors in each individual diagnostic model. This is done by providing a better correspondence and unified platform for different communities through a simplistic interpretable view via D-matrix. This will advance the field of ISHM to be cost-effective.

7. CONCLUSIONS AND FUTURE RESEARCH

The idea here is to promote D-matrix as the common framework to aid a simplified communication platform between system engineers and diagnostic modelers. Additionally, the knowledge transfer between different modeling techniques can be done via D-matrix. This will be instrumental to create a common model and also helps in improving each individual model. Also, this will help in achieving better diagnosis across all models by carefully choosing the best modeling technique, best representation of system design.

This paper focuses on initial steps in this process. The framework is laid out at the lower level. For this, we generated D-matrix from high fidelity physics model of cryogenic system. Then, the model is validated via iDME tool for effective diagnosis by proposing additional tests to tackle duplicate and hidden faults. In our future work, we will further analyze this system with more number of faults and tests. Also, the design of the physics model will be accordingly altered, thereby producing high efficiency diagnostics. We will also compare computational performance of D-matrix based inference algorithms to full-scale physics models. We will also consider propagation delays either as part of the model or inference algorithm.

Another key aspect of future research is to provide more information on what type of test needs to be designed and corresponding placement. We did not explore this field yet, but will be a good addition in our iDME framework. We further focuses on translating the analysis on D-matrix to original models, thereby making each model effective.

Single D-matrix may not be always sufficient to represent a system especially during transient state. Thus, it requires multiple D-matrices for system representation and inference. But, in this paper, we introduced to build a single D-matrix – aggregate of all multiple D-matrices corresponding to each system mode. Also, additional information may be required, for example couplings between faults. This extra information needs to be properly represented in addition to D-matrix for proper utilization across the board during inference. Our future research will focus on this aspect of how best to represent D-matrix and the additional information. We will also streamline this process for systems engineering. In summary, the goal of this proposed process is to make model-based diagnostic field cost-effective and ready for verification and validation during systems engineering process.

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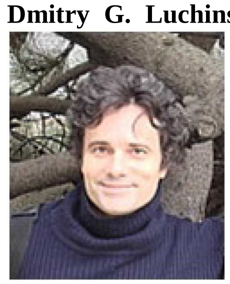

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APPENDIX

Fault	PT104High	PT104Low	TT104High	TT104Low	PT161High	PT161Low	TT162High	TT162Low	PT145High	TT146High	TT146Low	PT148High	TT149High	TT149Low	TT156High	TT156Low	TT191High	TT191Low
1_2	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
1_3	0	0	1	0	0	0	1	0	0	1	0	0	1	0	1	0	1	0
1_4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0
1_5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
2_1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2_2	1	0	1	0	1	0	1	0	1	1	0	0	0	0	0	0	0	0
2_3	0	0	1	0	0	0	1	0	0	1	0	0	0	0	1	0	1	0
2_4	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	1	0
2_5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
3_1	0	1	0	1	0	1	0	1	0	0	1	0	0	1	0	1	0	0
3_2	0	0	0	1	0	0	0	1	0	0	1	1	0	1	0	1	0	1
3_3	0	0	0	1	0	0	0	1	0	0	1	1	0	1	0	1	0	1
3_4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
4_1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4_2	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
4_3	0	0	1	0	0	0	1	0	0	1	0	0	1	0	1	0	1	0
4_4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0
4_5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
5_1	0	1	0	1	0	1	0	1	0	0	1	0	0	1	0	1	0	0
5_2	0	0	0	1	0	0	0	1	0	0	1	0	0	1	0	1	0	1
5_3	0	0	0	1	0	0	0	1	0	0	1	0	0	1	0	1	0	1
5_4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
6_3	0	0	0	0	0	0	1	0	0	1	0	0	1	0	1	0	1	0
6_4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0
6_5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
7_3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0
7_4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0