IMPROVING FAULT ISOLABILITY PROPERTIES BY STRUCTURAL ANALYSIS OF FAULTY BEHAVIOR MODELS: APPLICATION TO THE DAMADICS BENCHMARK PROBLEM

Erik Frisk [*], **Dilek Düştegör** [**],
Mattias Krysander [*], **and Vincent Cocquempot** [**]

[*] *Dept. of Electrical Engineering*
Linköping University, SE-584 31 Linköping Sweden
`{frisk,matkr}@isy.liu.se`
[**] *Université des Sciences et Technologies de Lille*
LAIL, UPRESA CNRS 8021, Bât. P2
59655 Villeneuve d'Ascq, Cedex, France
`{dilek.dustegor,vincent.cocquempot}@univ-lille1.fr`

Abstract: Structural analysis is a powerful tool for early determination of detectability/isolability possibilities. It is shown how different levels of knowledge about faults can be incorporated in a structural fault-isolability analysis and how they result in different isolability properties. The results are evaluated on the DAMADICS valve benchmark model. It is also shown how to determine which faults in the benchmark that need further modeling to get desired isolability properties of the diagnosis system.

Keywords: diagnosis, structural analysis, fault isolation, consistency relations

1. INTRODUCTION

Structural analysis is a powerful tool for early determination of detectability/isolability possibilities. This is important both to evaluate if the number and placement of sensors is adequate in order to meet diagnosis specifications.

Even though the structural information is very coarse, useful insights can be gained by analyzing the structure. This is also one of the strengths, since useful information can efficiently be obtained early in the development process before much work has been spent on obtaining detailed analytical models.

Structural analysis for FDI has been extensively studied, for example in (Staroswiecki et al., 2000; Pulido and Alonso, 2000; Krysander and Nyberg, 2002b). Furthermore, structural analysis has also proved useful in sensor-placement for FDI (Travé-Massuyès et al., 2001) and reconfigurability analysis

for fault tolerant control (Gehin et al., 2000). Here, the focus will be on fault isolability analysis.

Obtaining accurate models is expensive and difficult and this is especially true when models describing faulty behavior of the plant is considered. To obtain such models, experimental data from a faulty process or deep engineering knowledge and experience of process components are needed, neither of which may be present early in the development process. Therefore it is interesting to analyze the level of knowledge about specific faults that are needed to meet diagnosis requirements. Three levels of fault knowledge can be stated as:

(1) A basic level of knowledge is to only specify which component the fault influences. No specific information on how and in which constraints the fault influences the process is included. A component is regarded as a subset of the model equations.

(2) A second level of fault knowledge is when it is specified which equation or equations within a component description that is subjected to fault influences, i.e. which model equations that are (possibly) not valid in case of a fault.

(3) A third level is when additional information about the fault is available and a model for the fault signal is available. This could for example be that the fault size is slowly varying and can be assumed constant, or that the fault size is highly correlated with some other signals in the model.

To exemplify the above, consider a tube that is connected to a pipe and where we can have a leakage due to a loose connection between the two components. Basic knowledge is that a leak influences the equations describing the flow through the system. With a more detailed model, we know that a leakage results in an additional flow out of the system. Thirdly, it is possible that the effective area of the leakage is dependent on the pressure in the system due to elasticity in the plastic tubing.

In summary, it is valuable to get information of what level of knowledge about faults that is necessary to obtain sufficient fault isolability properties of the diagnosis system. Structural analysis is one tool to get such information.

2. STRUCTURAL ANALYSIS AND FAULT DETECTABILITY/ISOLABILITY

Structural analysis is concerned with properties of the system structure. Structural information here means which variables that appear in which equations/constraints. Now it will be briefly outlined how an analysis of the structural model can provide information on fault isolability properties of the model.

The types of variables in a structural model can in a diagnosis context be divided into

(1) known variables, typically measurements and controller outputs
(2) unknown variables, typically internal states and unknown inputs that should not influence the residual
(3) faults to be detected

The model is here represented by an incidence matrix which is a matrix where each row corresponds to an equation and each column to a variable. An X in position (i, j) indicates that variable j appears in equation i. Consider the small static model

$$g_1(x_1, x_2, u) = 0$$
$$g_2(x_2, y, f) = 0$$

consisting of two equations, two unknown variables x_1 and x_2, two known variables y, u, and one fault f. The incidence matrix representation is then

	x_1	x_2	y	u	f
g_1	X	X		X	
g_2		X	X		X

Now that representation of structural models has been introduced, fault isolability analysis of such models can be approached. The basis for diagnosis is redundancy. In consistency based diagnosis systems a crucial step is conflict recognition. Here conflicts are recognized by using precomputed consistency relations [1] where a consistency relation is a static or dynamic constraint on the time evolution of known variables of the process. A consistency relation can be formally defined as

Definition 1. (Consistency relation). Let x and y be unknown and known variables respectively. Then, a scalar equation $c(y) = 0$ is a consistency relation for a set of equations $H(x, y)$ if and only if for all y it holds that

$$\exists x. H(x, y) = 0 \Rightarrow c(y) = 0 \qquad (1)$$

and there is no proper subset of H that has property (1).

This means that relation $c(y) \neq 0$ is a test on inconsistency of equations $H(x, y)$ with measured data. The task of the diagnosis system designer is then to find a suitable set of such relations where different subsets of relations are invalidated by different subsets of faults. In this way, fault isolation can be achieved. This is often referred to as structured residuals.

Thus, to evaluate possible isolability properties of the model, fault sensitivity of all possible consistency relations need to be studied. Now a method is presented for performing such analysis based on the incidence matrix representation of the model. To proceed, a definition from (Krysander and Nyberg, 2002b) is needed.

Definition 2. (Minimal Structurally Singular, MSS). A finite set of equations E is structurally singular with respect to variables X if the number of equations is larger than the number of variables that appear in the equations, i.e. the set of equations is over determined with respect to X. The set E is a minimal structurally singular set if none of its proper subsets are structurally singular.

An MSS should here then be regarded as a set of equations with which it is possible to derive a consistency relation. But also, due to the minimality property, all equations must be used when deriving the consistency relation. With this definition it is possible to state (under some technical model assumptions not included here):

Theorem 1. Let $\{E_i\}$ be the set of MSS:s. Then there exists a consistency relation for a set of equations H if and only if

$$H = \cup_i E_i$$

PROOF. See (Krysander and Nyberg, 2002a). ∎

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[1] Consistency relations are often also called Analytical Redundancy Relations (ARR).

This result implies that the isolability properties of a system can be determined by only considering the fault sensitivities of the MSS:s. An algorithm not described further here, to compute all MSS sets and their respective fault sensitivity based on an incidence matrix can be found in (Krysander and Nyberg, 2002a).

After the set of MSS:s has been determined, isolability properties can easily be computed. Say, for example that two MSS:s are found that are sensitive to faults f_1 and f_2 according to Figure 1a. In a noisy and uncertain environment we have to

	f_1	f_2
c_1	0	X
c_2	X	X

(a) Fault incidence matrix.

	f_1	f_2
f_1	X	X
f_2	0	X

(b) Fault isolability matrix.

Fig. 1. Isolability analysis

threshold the residuals such that the probability for false-alarm is low. Thus, conclusions about faults can only be drawn when a residual is larger than its associated threshold. When residuals are below thresholds, no conclusion can be drawn in a sound way. This means that for example f_2 *may* invalidate consistency relations c_1 and c_2. Thus, a large enough fault f_2 will be isolated as f_2. However, no matter how large, a fault f_1 can not be separated from f_2. This is summarized in the fault isolability matrix in Figure 1b where an X in position (i,j) means that fault i can be interpreted as fault j, i.e. fault i can not be isolated from fault j.

Finally, a brief note on how time differentiation in dynamic systems is handled here. There are at least three different ways to represent time differentiated variables:

(1) Extend the model with equations describing how, for example, $x(t)$ is related to $\dot{x}(t)$ through the differentiation operator. This means that relations on the form

$$\dot{x} = \frac{dx}{dt}$$

is added for each variable that appear differentiated in the original model (Staroswiecki et al., 2000).
(2) Consider x and $\dot{x}$ to be separate variables and perform structural differentiation of the model (Krysander and Nyberg, 2002b).
(3) Consider x and $\dot{x}$ to be structurally the same variable and treat dynamic equations in the same way as static equations.

All three are possible choices, but for the isolability analysis performed here we use the third approach. Of course, time differentiated variables need to be represented if, in a second step, unknown variables are eliminated to form a consistency relation or a residual generator. Either of the two first suggestions above is possible and they both have advantages and disadvantages. This topic is not pursued further here.

3. ILLUSTRATION ON SMALL EXAMPLE

In this section, the structural analysis outlined in Section 2 will be applied to a small example model. In particular it will be shown how fault models can be introduced in the structural model to increase the fault isolability performance of the diagnosis system.

Now, consider the following small first-order dynamics model

$$\dot{x} = -(\alpha + f_1)x + u \qquad (2a)$$
$$y = x + f_2 \qquad (2b)$$

with two known signals, the control signal u and the measurement y. The model is subjected to two faults where f_1 represents a change in the known parameter α and f_2 a fault in the sensor. Assume that we want to design a residual sensitive to fault f_2 but not to fault f_1, i.e. we want to isolate fault f_2 from fault f_1. It is clear that, with the information given in (2), no such residual exists and further knowledge about the process is needed. Now, assume that we know that the fault f_1 is slowly varying or, for a given limited time window, approximately constant. This information can be stated as

$$\dot{f}_1 = 0 \qquad (3)$$

With this new information it is possible to design a residual such that any *constant* f_1 does not influence the residual, i.e. a residual generator exists that fulfills the design specification. This could for example be done by designing an observer, estimating both the state and the fault f_1 with $y - \hat{y}$ as a residual. Now follows a description on how this straightforward fact also can be seen using only structural knowledge.

Consider again model equation (2), where the fault f_1 is considered as an unknown to be decoupled, the structural model becomes

	x	f_1	u	y	f_2
e_1	X	X	X		
e_2	X			X	X

Here it is evident that no structurally singular/over determined subsystem exists since the system has two unknowns and only two equations. Inclusion of the fault model (3) gives the structural representation

	x	f_1	u	y	f_2
e_1	X	X	X		
e_2	X			X	X
e_3		X			

Now, equations $\{e_1, e_2, e_3\}$ form a minimal structurally singular set of equations. Since f_2 appears in the equations in this set, any consistency relation for this set of equations may be sensitive to a change in f_2.

Thus, the analysis above states that there exists a residual generator such that f_1 is decoupled and the

residual is sensitive to the fault f_2. Note that this is only a structural result, the particular form of the underlying analytical expression involved might make transformations into a residual generator impossible. However such topics are of course beyond what is possible to analyze using only structural models.

4. MODEL OF DAMADICS VALVE

In Section 5, isolability analysis is performed on the DAMADICS valve. Here, a brief introduction of the model is given. A schematic figure of the valve is shown in Figure 2 and consists of three main components: the control valve, by-pass valve, and a spring-and-diaphragm pneumatic servo-motor to operate the valve plug. The figure also shows an internal control loop that is used to increase the accuracy of the valve plug positioning. Measured variables of
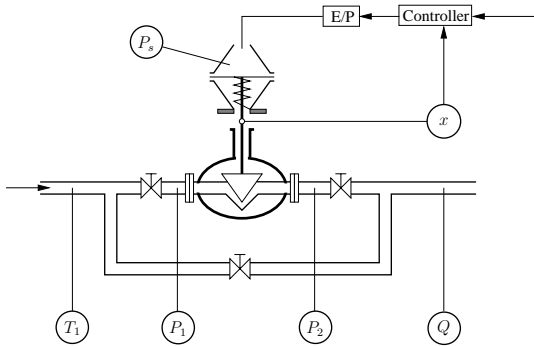

Fig. 2. Schematic figure of the DAMADICS valve

the valve, indicated by circles, are the valve plug position x, the fluid flow Q, fluid temperature T_1, up- and downstream pressure of the valve P_1, P_2, and the transducer chamber pressure P_s.

Details of this model is not included in this presentation, only the structure of the model is described. The presentation also shows the level of knowledge needed to make the analysis described and performed in Section 5. Readers interested in details of this model are referred to (WUT, 2002; Bartys, 2002; Bartys and Syfert, 2002) and the references therein.

4.1 Spring-and-diaphragm pneumatic servo-motor

This component consists of an electro-pneumatic transducer providing linear motion to the valve-plug. Thus, the equations in this component describe the dynamics of the valve plug and the transducer chamber pressure P_s, which provides the main driving force of the plug.

The relative valve position x is a dynamic function of the pressure in the chamber and the opposing force F_{vc}, the vena-contracta force, i.e.

$$x = f(P_s, F_{vc})$$

This equation includes a model of the spring in the transducer and also friction components in the driving force. The pressure in the transducer chamber

is a dynamic equation depending on the valve plug position (since this determines the effective volume of the chamber) and the net mass-flow of air Q_c into the chamber. The inlet flow is a, also dynamic, function of the valve plug position controller CVI output and the chamber pressure. Thus, these models can be summarized as

$$P_s = f(x, Q_c)$$
$$Q_c = f(P_s, CVI)$$

4.2 Control and bypass valve

The valve equation describes the flow past the valve, Q_v, and the vena-contracta force. Both these entities are functions of the pressure upstream, P_1, and downstream, P_2, of the valve, the fluid temperature T_1 and the valve-plug position.

$$Q_v = f(x, P_1, P_2, T_1)$$
$$F_{vc} = f(x, P_1, P_2, T_1)$$

The bypass valve is manually operated and only used when the flow past the control valve becomes choked. The flow past the bypass valve Q_{v3} obeys similar relations as the flow past the control valve.

$$Q_{v3} = f(x_3, P_1, P_2)$$

where x_3 is the position of the manually operated by-pass valve.

4.3 Fault modeling

In (Bartys and Syfert, 2002), detailed fault models are described for 19 faults acting on the valve and its components. Typical faults in the valve are valve clogging, leakages, sensor faults, and different fault acting on the dynamics of the servo. In total, the control valve, the servo motor, and the positioner has 7, 4, and 4 modeled faults respectively. In addition 4 general/external faults are modeled. The faults are denoted $f_1, \ldots, f_{19}$ according to the order above.

No descriptions of the faults are included here and the reader is referred to (Bartys and Syfert, 2002) for details. In the analysis done in Section 5, we focus on 14 out of the 19 faults [2].

4.4 Valve model summary

The number of model equations of course depends on what form and how many intermediate variables that are used when forming the model. Here, when the model equations were collected, the result of the modeling is 19 equations out of which 3 are dynamic. The variables in the equations include 15 unknown variables, 14 faults, and 9 known signals. The 9 known signals consists of 6 sensor signals, the valve-plug position controller reference value and output, and the position of the by-pass valve. The structure of the model is shown in Table 1.

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[2] Using the notation in (Bartys and Syfert, 2002), faults $f_2, f_3, f_6, f_{15},$ and f_{17} are not considered here.
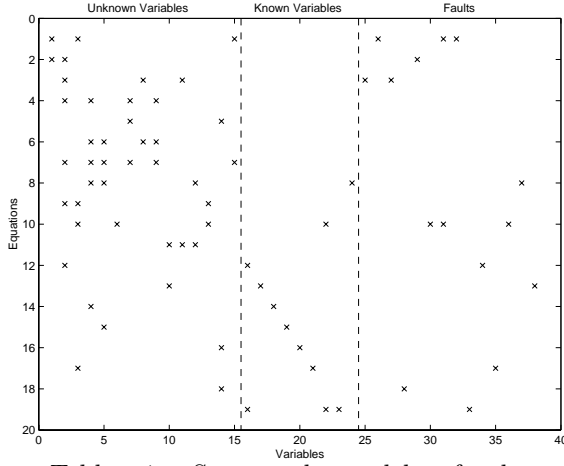
Table 1. Structural model of the DAMADICS valve.

5. VALVE MODEL ANALYSIS

This section will describe a structural fault isolability analysis of the valve model and also find where additional modeling effort is needed to increase isolability properties.

5.1 No decoupling of faults

First, only knowledge on which faults that appear in which equations is used in the analysis. This is only a first step, if isolability properties is not satisfactorily, the residuals can be structured, i.e. faults can be decoupled. Decoupling of faults is further pursued in Section 5.2 and Section 5.3.

First, all MSS sets are computed based on the structural model of the valve. When computing the MSS sets, no faults are considered as unknown disturbances to be decoupled and all differentiated variables are considered structurally equivalent to its non-differentiated version. This results in 15 MSS sets and for each MSS set, the fault sensitivity is computed. To visualize fault isolability properties of the computed MSS sets, a fault isolability analysis matrix is computed and shown in Table 2. To make

$$\begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Table 2. Fault isolability analysis matrix with fault variable order f_{16}, f_9, f_{19}, f_{18}, f_5, f_1, f_{14}, f_{11}, f_{10}, f_8, f_4, f_7, f_{12}, f_{13}.

the analysis more clear, a Dulmage-Mendelsohn

permutation is used to transform the fault matrix into an upper block-triangular form where isolability properties are clearly visible. Dulmage-Mendelsohn permutations only make sense in this case if row and column permutations are equal. This is not true in the general case, but due to the fact that the fault isolability matrix *always* has a non-zero diagonal, the row and column permutations are equal.

The fault sensitivity analysis first shows that faults f_{16} and f_9 is not detectable in any MSS, i.e. we need additional sensors to be able to detect these two faults. In the fault isolability matrix this implies that the first two rows, corresponding to f_{16} and f_9, have 1 in all positions. From the fault matrix we can draw additional conclusions that without any fault decoupling:

(1) The last three rows of the fault matrix show how faults f_7 (evaporation in the control-valve), f_{12} (fault in the electro-pneumatic transducer), and f_{13} (fault in the valve-plug displacement sensor) are isolable from all other faults without any further need of fault modeling or fault decoupling.
(2) The two blocks of 4 and 5 faults respectively show groups of faults that are isolable from each other but where individual faults within each group is not isolable from the other faults in the group.

Further isolability analysis is concentrated on the second block of faults

Fault	Description
f_4	Increase of valve or bushing friction
f_8	Twisted servo-motor piston rod
f_{10}	Servo-motor diaphragm perforation
f_{11}	Servo-motor spring fault
f_{14}	Pressure-sensor fault

5.2 Decoupling of faults

The next step in trying to increase isolability performance is to try and decouple faults in a group of un-isolable faults. If decoupling of one fault in the group of faults is possible without losing fault sensitivity to other faults in the group, isolability performance is increased. To analyze this, one fault at a time in the set $\{f_4, f_8, f_{10}, f_{11}, f_{14}\}$ is decoupled and the same analysis as in the previous section is performed. Performing these operations reveals that, in this case, the structure of fault influence is such that decoupling of the faults does not provide any additional isolability properties. The reason for this is that when decoupling one of the faults, any detectability of the other faults also vanishes and therefore also the possibility to isolate these faults from each other.

5.3 Decoupling of fault models with additional fault models

When decoupling of the faults, in a way outlined in the previous section, is not sufficient to achieve desired properties, additional information is needed.

One such way is of course to include additional sensors. If this is not possible, further modeling of the faults is a solution. Assume that, by engineering knowledge, such additional knowledge about the faults are obtained. In general this is an equation on the form

$$g(y, x, f) = 0$$

For example, if we know that the faults are slowly varying or approximately constant, relations on the form

$$\dot{f} = 0 \tag{4}$$

is added to the model equations. If the introduced fault model involves signals besides the fault signal, just introduction of the fault model might increase isolability performance. However, if the fault model is on the form (4) where only the fault signal is involved, additional decoupling is needed.

Here, model constraints on the form (4) is introduced. Performing the same decoupling procedure as in Section 5.2 a fault isolability matrix as in Table 3 is obtained. The conclusion from this is that with the

$$\begin{bmatrix}
1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\
1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\
0 & 0 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & \mathbf{1} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{1} & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{1} & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{1} & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{1} & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1
\end{bmatrix}$$

Table 3. Fault isolability analysis matrix after fault models are introduced. The variable order is the same as in Table 2.

additional fault models of faults f_4, f_8, f_{10}, f_{11}, and f_{14}, the structural analysis gives that it is possible to isolate the faults from each other.

6. CONCLUSIONS

This paper is concerned with structural isolability analysis of the DAMADICS valve model. It is shown how structural analysis can be used to assess isolability properties of a model. Since detailed knowledge about faulty systems is difficult to develop, it is essential to minimize this task. First, only information on which equations in the model that is influenced by the faults are provided. In Section 2 it is shown how structural analysis then provides information on which faults that need further modeling if the isolability objectives are to be met. It is also shown how additional fault models can be directly incorporated in the structural isolability analysis to ensure that the isolability objectives are met. The procedure is demonstrated in the DAMADICS valve model in Section 5 where it was concluded that 2 of the faults were not detectable with the set of sensors mounted on the valve. Three of the faults

were uniquely isolable and the rest of the faults were grouped into two sets of faults, isolable from each other but not from faults within each group. For faults in these two groups, it is shown how additional fault models increases isolability performance of the model.

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