State-based vs simulation-based diagnosis of dynamic systems

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Abstract.
In Model-Based Diagnosis there is an increasing interest in the diagnosis of dynamic systems. Some recent contributions in the literature show that in some cases such systems can be diagnosed with pure state-based diagnosis, i.e. reasoning on single states of the system rather than on transitions of the system from one state to another.

In this work we discuss how in a different context the same results do not hold, and show how reasoning on the causality in the system and using simulation can provide more precise diagnostic results with respect to state-based diagnosis.

Essential to this result are component fault models that characterize the discontinuity in the behavior associated with abrupt faults, i.e. the sudden transition of a component from the correct mode of behavior to a faulty behavior.

1 Introduction

In Model-Based Diagnosis [6] there is an increasing interest in the diagnosis of dynamic systems (e.g. [2, 9, 11, 12, 10, 14]), given that most of the technical systems that demand for some form of automated diagnosis are dynamic systems (in particular, systems with feedback provided by some automated control).

Some recent contributions in the literature present, on the one hand, results that show that a simple but paradigmatic dynamic controlled system can be diagnosed with pure state-based diagnosis, i.e. reasoning on single states of the system rather than on transitions of the system from one state to another [10]. Similar considerations have been provided in [5]. On the other hand, [14] presents some general conditions that ensure the equivalence of state-based and simulation-based diagnosis. Such conditions include the assumption that the system behaves continuously and that temporal constraints are the same for all behavior modes.

In this paper we compare state-based diagnosis with a simulation-based definition of diagnosis, which also takes into account the discontinuity in the behavior associated with abrupt faults, i.e. the sudden transition of a component from the correct behavior mode to a fault mode. Based on the causality in the system we impose constraints on such a transition, which are specific to each fault mode and violate the continuity conditions in [14] (in terms of [8] such constraints are "region transition" constraints).

Like the use of fault modes can eliminate spurious diagnoses [15], we show that this additional knowledge, which characterizes the dynamics of a fault, can significantly reduce the set of solutions with respect to state-based diagnoses, even under limited observability of the system.

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2 The example system and qualitative deviation modeling

We consider the controlled electric motor in [10] (see figure 1). The motor M, whose rotational speed is ω, is driven through a voltage v by the controller C which acts based on the desired speed d and the speed ω_m measured by the revolution counter S. Two versions of the controller are considered in [10]: a P-controller and a PI-controller; we consider the PI-controller version only.

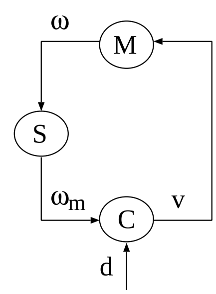

Figure 1. The example system.

The system can be modeled by the following equations, which include for each component a constant that is used to model also the faulty behavior of the component:

$$Motor: \quad T * \frac{d\omega}{dt} = c_M * v - \omega \qquad (1)$$

$$PI-controller: \quad \frac{dv}{dt} = c_C * (d - \omega_m) \qquad (2)$$

$$Sensor: \quad \omega_m = c_S * \omega \qquad (3)$$

where T is the inertia of the motor, c_M is the constant of the motor, c_C is the constant of the controller, c_S is the constant of the revolution counter. Faults can be characterized by deviations of such constants from their reference value.

In [10], in order to apply such a model for diagnosis, a corresponding model is derived that relates *qualitative deviations* of the variables in the model. For each variable x, its deviation is defined as

$$\Delta x(t) = x(t) - x_{ref}(t)$$

where $x_{ref}(t)$ is a *reference behavior* for x, which could be the evolution of x in case the system is not faulty (in which case it could be computed from quantitative model of the system and initial conditions), but could also be taken, as in [10], as some other reference value[3].

The **qualitative deviation model** is a model derived from the initial set of equations that relates the *signs* of variables and of their deviations. Denoting the sign of an expression E as $[E]$, there are rules for expressing $[E]$ and $[\Delta E]$ as an expression in sign algebra involving the signs of individual variables occurring in E and the signs of the deviations of such variables. For example, $[\Delta(a+b)] = [\Delta a] \oplus [\Delta b]$, where $\oplus$ is the addition in sign algebra. For derivatives, the notation ∂x is used for $[\frac{dx}{dt}]$, and $\partial \Delta x$ for $[\Delta \frac{dx}{dt}] = [\frac{d}{dt} \Delta x]$

The resulting qualitative deviation modeling for the motor system is the following:

$$[T] \otimes \partial\omega \oplus [\omega] = [c_M] \otimes [v] \tag{4}$$
$$[\Delta T] \otimes \partial\omega \oplus \partial\Delta\omega \oplus [\Delta\omega] = [\Delta c_M] \otimes [v] \oplus [\Delta v] \tag{5}$$
$$\partial v = [c_C] \otimes [d - \omega_m] \tag{6}$$
$$\partial\Delta v = [\Delta c_C] \otimes [d - \omega_m] \oplus [\Delta d] \ominus [\Delta\omega_m] \tag{7}$$
$$[\omega_m] = [c_S] \otimes [\omega] \tag{8}$$
$$[\Delta\omega_m] = [\Delta c_S] \otimes [\omega] \oplus [\Delta\omega] \tag{9}$$
$$\partial\omega_m = [c_S] \otimes \partial\omega \oplus \partial c_S \otimes [\omega] \tag{10}$$
$$\partial\Delta\omega_m = [\Delta c_S] \otimes \partial\omega \oplus \partial\Delta\omega \oplus \partial\Delta c_S \otimes [\omega] \tag{11}$$

(the term $[d - \omega_m]$ is left as is, since its value will be observed directly and then it will be more informative than $[d] \ominus [\omega_m]$). Diagnosis is then performed reasoning on the qualitative deviations, i.e. on *classes of faults*. For each component we consider a correct mode, with $[c] = [+]$ and $[\Delta c] = 0$ (where c is c_M, c_C or c_S), and three fault modes:

- c high: $[c] = [+]$ and $[\Delta c] = [+]$
- c low: $[c] = [+]$ and $[\Delta c] = [-]$
- c zero: $[c] = 0$ and $[\Delta c] = [-]$

A **mode assignment** assigns a (correct or faulty) behavior mode to each component.

3 Fault detection

We intend the reference behavior as the evolution of the non-faulty system[4]. In this case a diagnostic problem arises when a deviation of an observable variable is observed, i.e. the values of some of the variables in the qualitative deviation model are known and at least one of them is a non-zero value of a deviation.

We assume here that such a *fault detection* is performed independently of the qualitative deviation modeling; e.g. it is performed using a (maybe approximate) quantitative model, or, as in [14], it is provided by subjective observation of a human who detects that some variable is lower or higher than it should be.

In either case, there cannot be a perfect match between the actual state of the system and its observation in terms of qualitative deviations. This is because, e.g., a positive deviation means *any* positive value, but we cannot expect an arbitrarily small deviation to be detectable, e.g. due to noise and to imprecision in the estimation of numerical parameters in the model. This means that fault detection should be at least precise to detect the deviations that are large enough to be significant, e.g. expensive (estimating the expected cost due to malfunctioning or inefficiency in the system, with the associated risks). Providing methodologies for doing this is out of the scope of this paper. What we should at least assume is that fault detection, even if not *complete*, is *correct*, i.e. the deviations it detects *are* actual ones, even if not all the actual ones are detected.

The above issues are particularly significant for dynamic systems with automated control: some deviations could go undetected since the control subsystem compensates for them. Such deviations could moreover be slowly but constantly increasing.

Moreover, in a system with feedback (including controlled systems) it is possible that a deviation in a variable (due to a fault) will lead to deviations of most of the other variables. This will only occur through a sequence of qualitative states where the dynamics of the feedback effects is reproduced. The qualitative deviation equations, which, when everything was ok, were satisfied because all the deviations were zero, will now be satisfied because some deviation (due to the fault) is compensated by some opposite deviation (due to control). In principle, this situation could be detected e.g. by making the system work in some reference condition.

In the example system we will assume that deviations that can be observed are $[\Delta\omega_m]$ and $\partial\Delta\omega_m$, e.g. based on approximate knowledge of the correct behavior of the system which defines, for example, an envelope where the observed speed should be included, based on the target speed. A similar approach has been used to detect observations on a real system [1].

4 Defining diagnosis

A qualitative state assigns a qualitative value (in our case $[-]$, 0 or $[+]$) to all variables (including their deviations) and their derivatives. Let $\mathcal{S}$ be the set of all qualitative states. The model of the system is a set of equations and identifies a set $\mathcal{M} \subset \mathcal{S}$ of the states (those satisfying the equations). A mode assignment F corresponds to a subset of $\mathcal{S}$, denoted as $\mathcal{F}$, where the mode assignment equations are satisfied. A particular mode assignment is F_{ok} where all the components have the correct mode. A set of observations OBS, assigning a value to a subset of variables, similarly identifies a subset $\mathcal{OBS}$ of $\mathcal{S}$.

A mode assignment F is considered **consistent** with a set OBS of observations relative to a single state if $\mathcal{M} \cap \mathcal{F} \cap \mathcal{OBS} \neq \emptyset$.

In the following we *do not deal with time-varying faults*, that is, we assume that faults are permanent; moreover, we restrict the attention to single faults. This means that the system passes from the mode assignment where all components are ok to a mode assignment with a single fault and then remains, for the time it is observed, in the same mode assignment.

We also restrict the attention to a set of observations OBS in a single qualitative state. As we shall discuss later in more detail, this could be the first state where deviations are observed.

Even with such assumptions there can be several ways of defining whether a mode assignment F is considered to be a diagnosis for a set of observations OBS relative to a qualitative state.

As an example of observations we will consider the following (see figure 2): the measured speed is positive ($\omega_m = [+]$), it is below its target ($[d - \omega_m] = [+]$), it is increasing ($\partial\omega_m = [+]$) but it is less than it should be ($[\Delta\omega_m] = [-]$), and still diverging ($\partial\Delta\omega_m = [-]$).

[3] Actually, in [10], this choice is essential to diagnose with pure state-based diagnosis the system with the P-controller.

[4] Differently from [10].

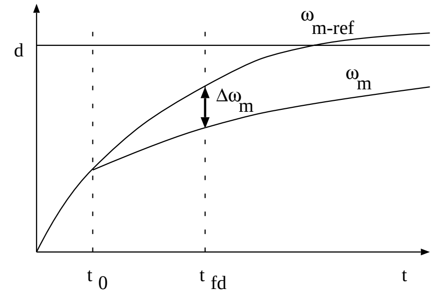

Figure 2. The example observation; t_0 is the (unknown) time when the fault occurs, t_{fd} is the time when it is detected

4.1 State-based diagnosis

A basic requirement is that F is consistent with the observations; that is, there exists a qualitative state S of the system that is consistent with F and OBS. State-based diagnosis reduces to this if there are observations on a single qualitative state. Therefore in our context we have the following definition.

Definition 1 State-based diagnosis. A mode assignment F is a state-based diagnosis if it is consistent with OBS, i.e. $\mathcal{M} \cap \mathcal{F} \cap \mathcal{OBS} \neq \emptyset$.

However, if we apply state-based diagnosis to our test case with the example observations, we get the following results.

- *Nearly all the single faults are consistent with the observations*; in particular, the resulting single fault candidates are: c_C high, c_C low, c_C zero, c_M high, c_M low, c_S high, c_S low. For example, "c_M high" satisfies the equations provided that $[\Delta v] = [-]$ and $\partial \Delta v = [+]$, that is, the control command is below its expected value, but approaching it.
- *Even the "ok" mode for all components is consistent with the observations*. (again, the equations are satisfied, provided that $[\Delta v] = [-]$ and $\partial \Delta v = [+]$). This fact is particularly significant. The strategy of a typical diagnostic algorithm could start by looking for conflicts in the set of assumptions that all components are in the ok mode, and in this case it would not find anything. In general, any diagnostic algorithm based on a preference for, at least, minimal diagnoses, would conclude that the best explanation here is that the system is working. There would be an inconsistency with fault detection which activated diagnosis based on the observation that something was going wrong.

4.2 Simulation-based diagnosis

Even if the "ok" mode is consistent with the observation, there is an argument that makes it counterintuitive as a diagnosis: in the mode where all components are in the ok mode, no deviation could possibly be caused, i.e. the state that is consistent with the ok mode and the observations cannot be reached from a state with no deviations. Moreover, any fault should lead to a typical dynamics in its manifestation; for example, "c_M high" should rather lead, at least initially, to a "too high" measured speed, rather than a too low one (as observed in the example).

Therefore, we consider the following idea for defining diagnosis for observations OBS relative to a qualitative state S. Other than requiring that S is consistent with the fault F and the observations, we require that such a state can be reached from a state S_0, consistent with the "all correct" mode assignment, and where all deviations are zero, through a sequence of states where the first one, S_1, results from "injecting" the fault into S_0, and the subsequent ones, up to S, are each one a successor state of the previous one according to qualitative simulation (see figure 3).

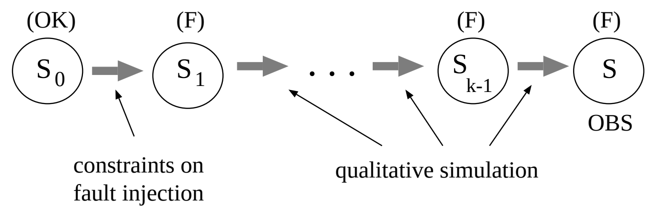

Figure 3. Defining diagnosis across time.

The relation of S_0 and S_1 must be modeled, as we shall see later, with appropriate constraints on the transition from a behavior mode to another (in particular, from the correct mode to a fault mode). Notice that S could coincide with S_1, and the initial conditions, i.e. the qualitative values of "non-deviation" variables, in S_0, may be known or not. Since the time where the fault occurs is not known, the quantitative values cannot be known[5], but a qualitative value could be known.

It could moreover be required that S is the first state in the sequence that is **detectable** by fault detection; i.e., in the sequence, no states could occur that would have been detected: diagnosis would have in fact been activated for that state rather than for S.

The definition of *detectable* could vary, depending on the assumptions on fault detection. In qualitative simulation there is at least a set of qualitative states that can only ideally be detected: those states which only last for a time point, rather than an interval, since a variable is at a landmark value (here the only landmark is 0) and its derivative is not zero. Directly observing these states (rather than hypothesizing them based on the subsequent states), which only last for a time point, is idealistic. We therefore adopt the following definition of "detectable" as a minimal one.

Definition 2 Detectable state. A qualitative state is detectable iff it has some non-zero deviation and it is an interval state in qualitative simulation.

We introduce the term **immediate fault detection** to denote the fact that any detectable state is detected (and then diagnosis is activated) before it ends. This justifies the requirement above on the sequence of states: that S is the first detectable state in the sequence.

Notice that the use of the term "immediate" *does not mean that any arbitrarily small deviation should be detected*, but only that a deviation is detected before the system changes its qualitative state to another one with some other deviation which *is* detected. This is similar to the condition in [10] that observations are *gapless*.

4.3 Constraints related to injecting a fault

As mentioned above, an important issue is to determine which state the system can move to, immediately after the occurrence of an

[5] Which is one of the reasons that prevents a quantitative simulation approach to be applied.

abrupt fault, i.e. the case where a system parameter changes abruptly (and, therefore, we assume, discontinuously) from its reference value to an abnormal value, and then its deviation changes from zero to a non-zero (not necessarily constant) value.

Of course the state resulting from such an abrupt fault must satisfy the system equations plus the additional constraint on the abnormal parameter, but it is evident from the examples that more constraints can be given based on the intuition of the causality of the system.

For an example from a different domain[6], consider a fluid container with incoming flow f_1, outcoming flow f_2 and pressure p. Its qualitative deviation equation is

$$[\Delta f_1] \ominus [\Delta f_2] \ominus [\Delta f_{leak}] = \partial\Delta p$$

where f_{leak} is the flow leaking out, whose reference value is 0. Consider the case where, starting from a state where all the deviations are 0, the container starts leaking, i.e. $[\Delta f_{leak}]$ changes from 0 to $[+]$. Notice that there are several possible ways of satisfying the equation given $[\Delta f_{leak}] = [+]$, and, in particular, there is more than one minimal change that restores the equation: $[\Delta f_1]$ becomes $[+]$, $[\Delta f_2]$ becomes $[-]$, or $\partial\Delta p$ becomes $[-]$, that is, the inflow increases, the outflow decreases, or the pressure starts deviating negatively. Intuitively, only the last case is a possible direct effect, i.e., can be the first state where the system moves to. The other changes *are* possible, especially if there is a pressure control system or anyway some compensatory effect; but such a control or compensation is only possible as a consequence of a (whatever small) negative change of the pressure "caused" by $\partial\Delta p = [-]$.

Several approaches exist for introducing this causal information, which is essential to an adequate representation of the behavior of the system. Some approaches for deriving the causal structure of a model have been introduced early in the qualitative reasoning community by de Kleer and Brown [4], and by Iwasaki and Simon [7] based on earlier work in the field of economics. In [12] a *temporal causal graph* is derived from a *bond graph*; the causality assignment rules for bond graphs are such that for a capacitor, the effort (pressure) is determined based on the flow. Therefore in an example (a bi-tank system) similar to the one considered here, the pressure in the container is determined based on the sum of flows; as a result, in the temporal causal graph, one flow can influence another only through the pressure[7].

Independent of how causal dependencies are derived, they are used in the same way in approaches for reasoning about actions and change. For example in [16] causal rules that relate a change to another change are derived from a more compact representation of knowledge, based on state constraints (whose equivalent here are the system equations) and *influence information*, that is, information on which "fluent" (variable) can directly influence another, in the sense that a change of the first may cause a change of the second. Influence information is analogous to causal ordering in [7]. Something similar can be provided in the example, stating that f_{leak} can only influence $\frac{dp}{dt}$. Therefore, if changing the influenced variables leads to satisfying the equation, these will be the only possible overall changes occurring as a side effect of the change corresponding to the abrupt fault. Usually, a variable does not influence more than another one, and there is only one value for the latter that restores the equation, therefore there is only one possible resulting state.

[6] This is a simplification of an example from a real system; the approach in the paper has been successfully applied to such a system.

[7] In particular, in the bi-tank example, the effect of a leak in the first tank would be the same as the one of a sudden decrease of the inflow, which leads in a subsequent state, due to an integration effect, to a change in the pressure at the bottom of the tank.

This methodology can be applied to the motor system as follows.

- In the motor equation, c_M only influences $\frac{d\omega}{dt}$; therefore, when the fault "c_M high " occurs, the only way of satisfying equation (5) is (assuming $[v] = [+]$) to have $\partial\Delta\omega = [+]$.
- In the PI-controller equation, c_C only influences $\frac{dv}{dt}$; therefore, when the fault "c_C high " occurs, the only way of satisfying equation (7) is to have $\partial\Delta v = ([d - \omega_m])$.
- In the sensor equation, c_S only influences ω_m; therefore, when the fault "c_S high " occurs, the only way of satisfying equation (9) is to have $[\Delta\omega_m] = [+]$, and the only way of satisfying equation (11) is to have $\partial\Delta\omega_m = \partial\omega$

Determining all possible dependencies allows to establish which (hopefully deterministic) side effects a fault gives rise to. Doing this for the example system, a sequence of deterministic side effects for each fault injection has actually been provided.

4.4 Definitions of simulation-based diagnosis

Based on the above approach to constrain the behavior of the system when a fault occurs, we introduce the following definition for stating whether a mode assignment F is a diagnosis for observations OBS (we again refer to figure 3).

Definition 3 Simulation-based diagnosis with immediate fault detection. Let $\mathcal{S}_{\Delta=0}$ be the set of states where all deviations are 0. Let $V_{\Delta obs}$ be the set of observable deviation variables, and $\mathcal{S}_{\Delta obs=0}$ be the set of states where all the members of $V_{\Delta obs}$ are zero. Let $\mathcal{S}_{context}$ be the set of states where the initial conditions have the known value (if any such value is known). Let $\mathcal{S}_P$ and $\mathcal{S}_I$ be the set of point states and interval states in qualitative simulation. F is a simulation-based diagnosis if there is a sequence of states $S_0, S_1, \ldots, S_k$ such that:

$$S_0 \in \mathcal{M} \cap \mathcal{F}_{ok} \cap \mathcal{S}_{\Delta=0} \cap \mathcal{S}_{context}$$

$$S_1, \ldots, S_{k-1} \in \mathcal{M} \cap \mathcal{F} \cap (\mathcal{S}_P \cup \mathcal{S}_{\Delta obs=0})$$

$$S_k \in \mathcal{M} \cap \mathcal{F} \cap \mathcal{OBS} \cap \mathcal{S}_I$$

$$inject(F_{ok}, F, S_0, S_1) \wedge next(S_1, S_2) \wedge \ldots \wedge next(S_{k-1}, S_k)$$

where "$next$" is the successor relation in qualitative simulation[8], and "$inject$" is the relation defined by fault injection constraints discussed above: $inject(F_{ok}, F, S_0, S_1)$ means that injecting F in S_0, where F_{ok} was holding, may lead[9] to S_1.

Notice that the "immediate" fault detection requirement corresponds to the constraint that intermediate states are not detectable, i.e. they are either point states or states with no deviation for observable variables.

4.5 Results on the example system

In the example we assume the same set of observations as above, i.e. $[\Delta\omega_m] = [-]$, $\partial\Delta\omega_m = [-]$, $\omega_m = [+]$, $\partial\omega_m = [+]$, and $[d - \omega_m] = [+]$; moreover, we assume as initial conditions the same values for non-deviation variables, i.e. $\omega_m = [+]$, $\partial\omega_m = [+]$, and

[8] In particular, we have experimented a constructive notion of qualitative simulation also based on the causal dependencies [13].

[9] Or "leads", if the relation is functional in its 4th argument as in the examples. Moreover, the first argument of the relation may be omitted if we only define constraints relative to injecting a fault in the F_{ok} mode.

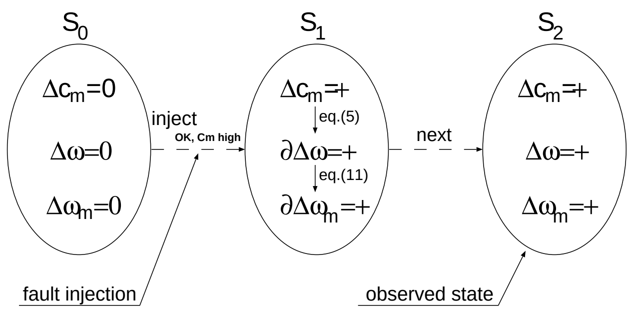

Figure 4. Rejecting fault c_M high.

$[d - \omega_m] = [+]$. This means assuming that when the fault occurred, the measured speed was positive, increasing and below its target, which makes sense in the situation in figure 2 even if the exact time when the fault occurred is unknown.

The "ok" mode for all components is not a simulation-based diagnosis for this case, since starting from a state with no deviation, and injecting no fault, no state with non-zero deviation can be reached, including the state S to which observations are relative.

The simulation-based single fault diagnoses, assuming immediate fault detection and the above initial conditions, are **just 3 out of the 7 state-based diagnoses**: c_C low, c_M low and c_S low. For example, "c_M high" is discarded because it predicts the evolution in figure 4, where the fault injection leads to state S_1, where $\Delta c_M = [+]$ implies, given the causality constraints associated with equation 5, $\partial \Delta\omega = [+]$, and, being the sensor ok, $\partial\Delta\omega_m = [+]$, due to equation 11. This leads to S_2, where $\Delta\omega = [+]$ and $\Delta\omega_m = [+]$. This positive deviation of the measured speed should have been detected before the negative deviation that activated diagnosis. A similar sequence, with opposite (i.e., negative) deviations, shows that "c_M low" is a diagnosis.

5 Discussion

In this paper we presented results in an opposite direction with respect to the ones in [10, 14]: we showed, on a variation of an example from those papers, that simulation may actually be useful to restrict the set of possible diagnoses. Similar results have been obtained in a test case regarding a dynamic, automatically controlled subsystem of a real industrial system [1].

With respect to the experimental results in [10], we use a different definition of the reference behaviors; the one in [10] is shown to be useful for diagnosing the system with the P-controller, but observing the second-order derivative is necessary for the PI-controller.

With respect to the general results in [14], there is a fundamental difference here: the temporal constraints are not *continuous* (in the sense of [14]) exactly because of the constraints on fault injection, that capture an inherent discontinuity in the behavior of the system: the occurrence of an abrupt fault. Moreover, such transition constraints are specific of each fault, i.e. different fault modes are not *homogeneous* (again in the sense of [14])

[14] also mentions a way of enhancing the results of state-based diagnosis by enriching the observations, using the same kind of inferences used in qualitative simulation, i.e. reasoning on continuity and derivatives. In particular, the idea is that if, e.g., a positive deviation of v is observed, which was 0 before, there must be a state in between where both the deviation of v and its derivative are positive. The results shown above for state-based diagnosis assume that such an inference has already been done, in fact they also provide the deviation of the derivative in the observations.

Of course, an advantage of state-based diagnosis would be its efficiency, since simulation-based diagnosis should perform a search in the state space in order to rule out a fault. However, in [13] we show that using causal dependencies in simulation allows us to make such a search feasible (as in [12]; the causal structure is used to speed-up simulation also in [3]). Moreover, as in [1], where an on-board monitoring and diagnosis system should react promptly as soon as some deviation is detected, such a search can be performed off-line, precompiling the results into a decision tree to be used on-line.

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