There Are no Hybrid Systems A Multiple-Modeling Approach to Hybrid Modeling

Peter Struss

Model-based Systems and Qualitative Reasoning Group of the Technical University of Munich,
Orleansstr. 34, 81667 München, Germany
OCC'M Software GmbH, Gleissentalstr. 22, 82041 Deisenhofen, Germany
struss@in.tum.de

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Abstract

There are no hybrid systems, there are only hybrid models. Whether or not a change is modeled as a continuous or discontinuous one, depends on the purpose of the model. A proper treatment of hybrid models is, hence, a matter of multiple modeling and model abstraction and approximation. More specifically, a proper theory of hybrid models has to be a theory of temporal (or behavioral) abstraction and approximation. The primary problem is: How and under which circumstances can we transform a continuous change into a discontinuous one and vice versa? The core of this question is whether or not a certain distinction is significant. This depends on the context which includes the overall system and the purpose of its modeling. The paper deals with the problem of deriving the sets of qualitative values of model variables that allow to generate the distinctions required by the goal of model based prediction and the structure of the system. We present a formal definition and analysis of the problem and an algorithm for computing appropriate qualitative values based on propagation of distinctions. We outline how this generic solution can be used for deriving models of time scale abstraction including discontinuous changes.

Introduction

There are no hybrid systems, there are only **hybrid models**. Whether or not a change is modeled as a continuous or discontinuous one, depends heavily on the purpose of the model.

Although many people dealing with hybrid modeling will not have severe difficulties agreeing with this view, they will still find it "natural" to describe the opening and closing of valves in an Anti-lock Braking System (ABS) as instantaneous, while the de-acceleration of the car is seen as a continuous change. It is "natural" only under certain preconditions and goals, for instance, from the perspective of a driver who is interested whether or not the car will stop in time. Designers of the ABS hydraulics might be punished if they disregard that it takes a while until the valve is really open.

To illustrate the relativity of changes by a more naive example which has been used in (Iwasaki 92), we consider a block that is forced to slide back and forth on a surface of, say, soft wood (Fig. 1). The sliding of the block will wear out the surface which results in a reduction of the elevation z_s of the surface. How to describe this change?

- A first view could be that the wearing of the surface is so slow, that z_s can be considered constant: the table's tabletop is 5cm and hardly affected by the wearing (Fig. 2a).
- On the other hand, the block affecting only a small strip
 of the table, and in comparison with its environment, we
 can feel a dent which we check to be steadily deepening
 over a number of weeks (Fig. 2b).
- However, the deepening is not steady, because it happens only if the block slides on the measured section and, hence, occurs in steps (Fig. 2c).
- Which is not true, because it starts when the block starts sliding on the section and continues until it has left it (Fig. 2d).
- If we yet look closer, the wearing is not continuous, but happens through breaking off of small particles (Fig. 2e).

At this point, measurement of z_s as a well-defined quantity may be considered questionable, and we stop.

What this stupid little example demonstrates, is

- there are changes possible both from models with continuous changes to discontinuous ones and vice versa. A proper treatment of hybrid models is, hence, a matter of multiple modeling and model abstraction and approximation. More specifically, a proper theory of hybrid models has to be a theory of temporal (or behavioral) abstraction and approximation.
- that the process has no inherent fixed ,,temporal granu-

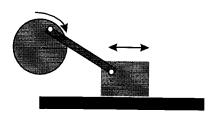


Figure 1 The sliding block

larity" that we could associate with the respective model fragment. The primary problem is: **How** and **under which circumstances** can we transform a continuous change into a discontinuous one and vice versa?

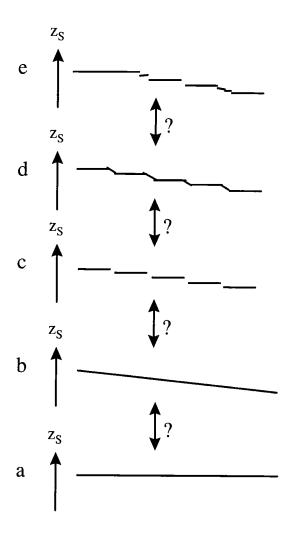


Figure 2 How does z_S change?

The "How?" has received some attention in the qualitative modeling community, but by now there exists no general answer. "Under which circumstances?" is a question that has attracted less research, although it is a fundamental challenge for model-based systems. This is because it challenges the idea of libraries of local re-usable (component) models, which is essential to the potential benefit provided by model-based systems.

Building models of families of complex technical systems is economically feasible only if they can be composed from elementary building blocks that can be re-used for many systems and purposes. This requires that the model fragments in the library are stated in a way that has little or no dependency on a particular context and purpose of the

model. But the example demonstrates that this is not possible.

The only way out is to develop methods for **generating** the models that are appropriate for a given context from a more basic model, for instance by transforming it after an initial composition step.

Hybrid modeling can thus be regarded as an instance of a more general problem. The core of this problem is whether or not a certain distinction in a model is **significant**. In the case of hybrid modeling and temporal abstraction, this concerns the question whether or not

- its magnitude, and/or
- its duration is considered significant, or
- its speed does not significantly deviate from infinity.

What has to be considered a significant distinction is determined by the context which includes the **overall system** and the **purpose of its analysis**.

The task we are addressing in this paper is: Given

- a system that is composed of some constituents and
- a certain goal of its modeling, furthermore
- a "base model" of the constituents that defines the achievable granularity of distinctions,
- initial distinctions of values of variables that are required by models of individual constituents (e.g. thresholds that determine changes in the operating mode) and
- initial distinctions required by the goal of modeling (e.g. computing whether or not the vehicle will stop in time),

determine the distinctions to be made in the model that are significant w.r.t. the initially given distinctions. As a result, we can then transform the base model into the most abstract one that is still able to derive the distinctions we are interested in (provided the base model does).

In the next section, we will formally define this goal as a desired qualitative abstraction of the variable domains. We will then characterize these abstractions which forms the basis for their computation (algorithms are presented in (Struss and Sachenbacher 99)).

We will then show how this general formalism can be specialized for the case of temporal abstraction and hybrid modeling.

Distinguishing Qualitative Domain Abstractions

Formalizing the Goal

The first step is to state our goal precisely and formally. We will define it in a fairly general way. In particular, we do not only treat models composed of continuous functions, but relational models. Accordingly, a model of a system, S, to be analyzed is given by a relation

$$R_s \subset DOM(\underline{v}_s)$$
,

where \underline{v}_S is the vector of all parameters and variables (input, output, internal and state variables) in the system.

In this formalism, our problem can be stated as follows: there is

 a base domain DOM₀(v_i) for each variable v_i, (e.g. real numbers, intervals reflecting precision, but also states or a qualitative domain) and a model

$$R_{s,o} \subset DOM_o(\underline{v}_s)$$

= $DOM_o(v_1) \times DOM_o(v_2) \times ... \times DOM_o(v_n)$,

• a characterization of the primary distinctions for each v_i required for some external reason (a functional specification, safety limits, diagnostic distinctions etc.) or due to the structure of the local model, expressed in $DOM_0(v_i)$. More precisely, for a variable v_i , such distinctions are specified as partitions $\Pi=\{P_k\}$ of $DOM_0(v)$. A partition $\{P_k\} \subset P(DOM_0(v))$ (the power set of the domain) is a set of non-empty disjoint subsets that together cover the entire domain:

$$\forall P_k : P_k \neq \emptyset$$

 $P_k \cap P_1 \neq \emptyset \implies P_k = P_1 \text{ and } \bigcup P_k = DOM_0(v)$.

The intuition behind the partitions is that they define qualitative values: exactly values in different partitions P_k have to be distinguished from each other. In our example, the output voltage of the switch has the primary partition $\Pi_{vswitch} = \{\{0\}, (0, \infty)\}$. If for some v, there are no primary distinctions to be made, the partition is the trivial one:

$$\Pi = \{DOM_n(v)\}$$
.

In the following, it is often convenient to talk about the mapping of values to qualitative values, which we call qualitative domain abstraction.

Definition (Qualitative Domain Abstraction)

A qualitative domain abstraction is a mapping

$$\tau \colon DOM_{_{0}}(v) \to DOM_{_{\alpha}}(v) \subset P(DOM_{_{0}}(v))$$
 where $\forall \ v_{_{0}} \in DOM_{_{0}}(v) \colon v_{_{0}} \in \tau(v_{_{0}})$.

Remark: A qualitative domain abstraction is a domain abstraction in the sense of (Struss 92) and induces an abstraction of the system model by

$$R_{s,\tau}:=\tau(R_{s,0})$$
.

There is an obvious correspondence between domain abstractions and partitions: a qualitative domain abstraction τ of $DOM_0(v)$ induces a partition

$$\Pi_{r} = \tau(DOM_{o}(v))$$
,

and vice versa. By π , we denote the qualitative domain abstraction induced by the primary partition:

$$\pi:=(\pi_1, \pi_2, \dots \pi_n): DOM_0(\underline{v}_S) \to \Pi_1 \times \Pi_2 \times \dots \times \Pi_n$$

Variables that do not have any primary distinction associated, are mapped to the trivial partition, i.e. there exists only one "qualitative value" which represents the entire domain. Our view is that all we are ultimately interested in when using the model is optimal information about the

primary distinctions, and that other distinctions should be considered if and only if they are necessary to derive conclusions about the primary ones. From the initial fine-grained model $R_{S,0}$, primary distinctions can be determined by applying π .

What does it mean to "use the model"? It means, given information on some parameters or variables (through measurements, design choices, etc.), to determine resulting restrictions on other parameters and variables. If, for instance, measurements MEAS for some variables with the granularity of the respective DOM $_0$ are given, we can compute the resulting restriction $R_{S,0} \cap MEAS$. But only the primary distinctions implied by this restriction matter, i.e.

$$\pi(R_{s,o} \cap MEAS)$$
.

 $R_{S,0}$ may not be able to determine all required distinctions. But w.r.t. the possible ones, $DOM_0(\underline{v}_S)$ may be overly detailed. We would like to determine the distinctions to be made for each v_i that are both necessary and sufficient in order to express the model in terms of these distinctions only without losing the "distinguishing power" of $DOM_0(\underline{v}_S)$. This means: finding a qualitative domain abstraction for $DOM_0(\underline{v}_S)$

$$\tau = (\tau_1, \tau_2, ..., \tau_n)$$
where $\tau_i : DOM_n(v_i) \rightarrow DOM_n(v_i) = P(DOM_n(v_i))$

which is maximal in some sense but does not destroy the primary distinctions. This means: if there is any external restriction on the system behavior (actual observations, design specification, etc.), applying the qualitative domain abstraction τ before determining the primary distinctions does not change the result, formally: if the external restriction is given by a relation $R_{ext} \subset DOM_0(v_S)$, then

$$\pi'(\tau(R_{ext}) \cap \tau(R_{s,0})) = \pi(R_{ext} \cap R_{s,0})$$
. (1)

Here, π' : $\tau(DOM_0(v_S)) \rightarrow \Pi_1 \times \Pi_2 \times ... \times \Pi_n$ maps the results of the qualitative domain abstraction τ (i.e. sets) to the primary partitions they are contained in:

$$\pi'(\tau(v)) = \pi(v)$$
 for $v \in V$.

Obviously, this is well-defined only if τ is a refinement of π according to the following definition.

Definition (Refinement and Merge of Partitions and Domain Abstractions)

Let Π_1 , Π_2 in DOM₀(v) be two partitions. Π_1 is called a refinement of another one, Π_2 , iff

$$\begin{array}{ccc} \forall \ P_1 {\in} \ \Pi_1 & \exists \ P_2 {\in} \ \Pi_2 & P_1 {\subseteq} \ P_2 \ . \\ \text{It is called a strict refinement, if, additionally,} \\ \exists \ P_1 {\in} \ \Pi_1 & \forall \ P_2 {\in} \ \Pi_2 & P_1 {\neq} P_2. \end{array}$$

The merge of two partitions Π_1 , Π_2 of $DOM_0(v)$ is the partition containing all intersections of their elements:

$$\operatorname{merge}(\Pi_1, \Pi_2) := \{ P_1 \cap P_2 \mid P_1 \in \Pi_1 \land P_2 \in \Pi_2 \} \setminus \{\emptyset\} .$$

We apply the same terminology to the qualitative domain abstractions induced by the partitions.

Property (1) guarantees that we can first abstract both the model and the measurements and still are able to detect the same primary distinctions as before:

$$\pi'(\tau(R_{s,0}) \cap \tau(MEAS)) = \pi(R_{s,0} \cap MEAS) \; .$$

¹ In the following, when considering an arbitrary variable, we drop the index to improve readability.

Figure 3: Relationship of primary and induced qualitative domain abstractions

Figure 3 illustrates the situation. This analysis justifies the following definition of our target:

Definition (Distinguishing Qualitative Domain Abstraction)

Let $R_{S,0}$ in $DOM_0(\underline{v}_S)$ be the original fine-grained model of a system S and, for each variable v_i , a finite set of primary distinctions be given as a partition $\Pi_i = \{P_{ik}\}$ of $DOM_0(v_i)$. A qualitative domain abstraction

$$\tau: DOM_0(\underline{v}_s) \to P(DOM_0(\underline{v}_s))$$

is distinguishing w.r.t. $\{\Pi_i\}$ iff it is a refinement of π and

$$\forall \mathbf{R}_{ext} \subset \mathbf{DOM}_{0}(\underline{\mathbf{y}}) \\ \pi'(\tau(\mathbf{R}_{ext}) \cap \tau(\mathbf{R}_{s,0})) = \pi(\mathbf{R}_{ext} \cap \mathbf{R}_{s,0}) . \quad (1)$$

A distinguishing domain abstraction τ is **maximal**, if there is no distinguishing qualitative domain abstraction τ ' that makes less distinctions w.r.t. one $DOM_0(v_i)$, i.e. there is no τ_i that is a strict refinement of any τ'_i .

An important and common specialization of distinctions and of the task of finding maximal qualitative domain abstractions is obtained if qualitative values are given as intervals of ordered domains of variables. In this case, we can represent qualitative values in a compact way by their boundaries, the "landmarks" as opposed to an extensional representation of sets.

Definition (Landmark partition)

Let $DOM_0(v)$ be a totally ordered domain for a variable v. For a landmark set

$$L=\{l_k\} \subset DOM_0(v) \text{ with } k < m \Rightarrow l_k < l_m$$

the induced partition

$$\Pi_{l} = \{\{l_{k}\}\} \cup \{(l_{k}, l_{k+1})\}$$

is called a landmark partition.

In this case, we can hope for a compact representation of partitions, and, if there are (piecewise) monotonic functional dependencies among variables, also an easier way of computing maximal distinguishing qualitative domain abstractions.

Now that we have defined our goal, i.e. maximal distinguishing domain abstractions, we will characterize the desired solution in a formal way.

Characterizing Maximal Distinguishing Abstractions

The intuition behind the formal characterization of the desired qualitative domain abstractions is that property (1) can be established if the qualitative domain abstraction τ_j of **each single** $DOM_0(v_j)$ reflects the primary distinctions π_i of **any other** $DOM_0(v_i)$ (of course, including its own). This means, we apply τ to one $DOM_0(v_j)$ at a time only (leaving the other variables at the granularity of DOM_0) which corresponds to the mapping

$$(id_1, ..., id_{i+1}, \tau_i, id_{i+1}, ..., id_n)$$
,

where id_k is the identical mapping on $DOM_0(v_k)$. Then we determine the primary distinctions by the mapping

$$\pi^{"}_{\ j} = (\pi_{l}, \ ... \ \pi_{j-l}, \ \pi^{'}_{\ j}, \ \pi_{j+l}, \ ..., \ \pi_{n})_{\ ,}$$
 and (1) implies

$$\forall i,j \quad \operatorname{pr}_{i}(\pi^{"}_{j} (\tau^{"}_{j}(R_{ext}) \cap \tau^{"}_{j}(R_{s,0})) = \operatorname{pr}_{i}(\pi(R_{ext} \cap R_{s,0})),$$
 (2)

where pr_i is the projection to the i-th variable. On the other hand, if (2) holds, then (1) can be proved. This motivates a characterization of distinguishing qualitative domain abstractions starting from the question: Which distinctions in $DOM_0(v_j)$ are necessary in order to guarantee the determination of the primary distinctions in $DOM_0(v_i)$ under the assumption that all other variables can make distinctions given by DOM_0 ?

Given the primary distinctions for some $DOM_0(v_i)$, we have to determine which values in $DOM_0(v_j)$ can be aggregated into one qualitative value. The answer is that we can aggregate two values $v_{j,1}$, $v_{j,2}$ in $DOM_0(v_j)$ if they always lead to the same conclusions for the primary distinctions of $DOM_0(v_i)$, regardless of any additional restriction on other variables. This idea is captured by the following equivalence relation on $DOM_0(v_i)$.

Definition (Induced Partition)

Let an equivalence relation on $DOM_0(v_i)$ be defined by

$$\begin{array}{c} v_{_{j,l}} \approx_{_{j}} v_{_{j,2}} : \Longleftrightarrow \ \forall \ i,k \quad pr_{_{j}}(\{v_{_{j}} = v_{_{j},_{1}}\} \otimes R_{_{S,0}} \otimes \{v_{_{i}} = P_{_{ik}}\}) \\ = pr_{_{j}}(\ \{\ v_{_{j}} = v_{_{j,2}}\} \otimes R_{_{S,0}} \otimes \{v_{_{i}} = P_{_{ik}}\})\ , \ (3) \end{array}$$

where $pr_{.j}$ denotes the projection that eliminates the j-th variable, and for two relations R_1 , R_2 , the join $R_1 \otimes R_2$ is the intersection of the relations after their embedding into the domain of all occurring variables.

The sets of partitions $\Pi_{ind,j}$ for $DOM_0(v_j)$ given by the equivalence classes of the relations \approx_i ,

$$\Pi_{\text{ind,i}} := \text{DOM}_0(v_i) \big|_{z_i}$$

are called the partitions induced by the primary distinctions.

This means: two values are in different equivalence classes if and only if they entail different conclusions for at least one P_{ik} (i.e. refuting it or not), possibly together with additional information on other variables. This leads to the following characterization.

Lemma (Characterization of Maximal Distinctive Domain Aggregations)

The set of induced partitions { $\Pi_{ind,j}$ } defines a maximal distinguishing qualitative domain abstraction τ_{ind} w.r.t. to the primary distinctions.

The Special Case of Ordered Domains and Continuous Functions

So far, we considered relational models in general. This subsumes the case that a relation represents a functional dependency among variables. In particular, the functions involved may be considered as continuous functions. The notion of continuous functions can be applied to variables whose domains are ordered and, in particular, to abstractions of real-valued functions (see e.g. (Struss 93)).

A relation modeling the behavior of a constituent (e.g. component) of a system may involve both discrete and continuous variables and, thus, represent a set of continuous functional dependencies (at most one for each tuple in the cross product of the values of the discrete variables) and possibly a set of constraints on the discrete variables.

For instance, a model $R_{valve} \subset DOM_0((A, p_1, p_2, q))$ of a valve relating the opening A, pressures p_i and flow q could be

$$\begin{array}{l} R_{valve} \!\! := \{0\} \times DOM_0(p_1) \times DOM_0(p_2) \times \{0\} \cup \\ \{A_{max}\} \times \!\! \{(p_1, p_2, q) \mid q = \!\! k^*A^* sqrt(p_1 \!\! - \!\! p_2)^* sign(p_1 \!\! - \!\! p_2)\} \end{array}$$

which means that a transition between the open and the closed state of the valve is considered discrete.

In such a case, computing the induced partitions has to be done for the discrete variables (A in the example) as determined by (3) or (3'). For the continuous ones, we can exploit their functional dependencies at least when applying (3'): we do not have to compute the entire projection

$$pr_i(R_{S,0} \otimes P_{ik})$$

for all P_{ik} . This projection is a set of intervals in $DOM_0(v_j)$, and it suffices to compute the boundaries of each interval for each P_{ik} that represents a set of discrete values or a landmark of a continuous variable. In case of a monotonic function, it suffices to compute the absolute minima and maxima of the projections corresponding to landmarks, because the projections are intervals (note that, due to potential different granularity of the domains, a landmark of one variable may map to a contiguous set of values of another variable).

If we have a simple functional dependency of two variables, y = f(x), the task reduces to generating landmarks of y as the images of the landmarks of x:

 $\begin{array}{c} f(L_x) \text{ subset } L_{dist,y} \,, \\ \text{and vice versa:} \end{array}$

 $f'(L_y)$ subset $L_{dist,x}$.

Deviation Models

In many cases, for instance in diagnosis and FMEA, what makes a distinction in a model of a component is not determined by some absolute values of other variables, but by the fact whether or not it enforces a significant **deviation** on them, regardless of what their specific value is. The view is here that the function of the overall device imposes a certain tolerance on the output of this device, and its components are not considered faulty unless their behavior causes a disturbance of the output beyond the given tolerance. If we succeed to compute the tolerances of the parameters of the component models starting from the given functional specification, we can automatically generate fault models that reflect the particular device and its context, which we cannot expect by definition from generic models.

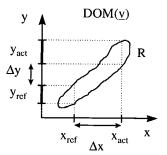


Figure 4: A relational model can impose constraints on the deviations of variables

The idea underlying deviation models is to describe deviations of variables which are consistent with a certain behavior model (Figure 4). For this purpose, we define

$$\begin{split} &\underline{\Delta}: \mathrm{DOM}_0(v) \times \mathrm{DOM}_0(v) \to \mathrm{DOM}_0(v) \\ &\underline{\Delta}((x_1, x_2, ..., x_n), (y_1, y_2, ..., y_n)) := \\ &(\Delta_1(x_1, y_1), \Delta_2(x_2, y_2), ..., \Delta_k(x_n, y_n)) = (x_1 - y_1, x_2 - y_2, ..., x_n - y_n) \end{split}$$

The deviation model of R, denoted R_{Δ} , describes how deviations of variables propagate through a component:

$$\begin{split} R_{_{\Delta}} &\subseteq DOM_{_{0}}(\underline{v}) \times DOM_{_{0}}(\underline{v}) \times DOM_{_{0}}(\underline{v}) \times DOM_{_{0}}(\underline{v}) \\ R_{_{\Delta}} &:= \{(\underline{v},\underline{v}',\underline{\Delta}(\underline{v},\underline{v}') \mid \underline{v},\underline{v}' \in R \ \} \end{split}$$

The projection of R_Δ on the Δv_i , $pr_{\Delta vi}(R_\Delta)$, can be viewed as a "pure" deviation model which relates deviations of variables independent of their actual and reference value. This is meaningful only in some cases, for example, if the relation describes a monotonic function. In general, at least information about the actual value will be necessary. The analysis of significant distinctions developed above can be applied to such deviation models: we can specify what is considered to be a significant deviation of some relevant variables by landmarks of the respective Δ -variable. They will induce partitions for other respective Δ -variables, but can also propagate to the domains of the variables themselves..

For instance, when the model is meant to be used for diagnosis purposes, the thresholds of tolerance of the variables that represent the overall functionality of a system will determine the distinction between the correct behavior of a component and a fault (which results in a violation of a threshold).

Temporal Abstraction

Finally, we return to the problem of determining the significance of changes. What can the formalism developed in the previous sections provide in this case?

First, we could explicitly specify landmarks for the derivatives of variables above which no distinctions should be made. The effect is that a change with a speed above this threshold is not distinguished from an infinitely fast change and, furthermore, that an additional limited influence does not affect the result, even if it is counteracting. Second, by specifying initial landmarks for Δ -variables, a change in the respective variables can be determined as insignificant.

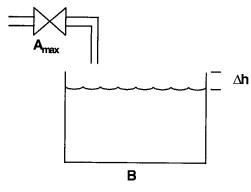
Deciding that a change is insignificant can require integration. The result of the change does not only depend on the derivative, but also on the duration of the change. This means, that **time** has to be **included as a variable** in the model. This will allow to determine distinctions on duration given some initial distinctions of affected variables or of their deviations, i.e. determine an appropriate temporal granularity. This forms the basis for the concept of a negligible duration and, hence, discrete changes.

But we can also specify initial distinctions on duration which will then induce appropriate qualitative abstractions of changing variables. To enable such inferences, integration constraints have to be made explicit and part of the model relation.

When we want to open a valve in order to fill a container at least up to Δh below the top, but avoid overflow in any case (Fig. 5), can we model the opening as a discontinuous change? The answer is general and unique: *It depends!* It depends on Δh , the maximal opening, A_{max} , the speed of opening it, da, the size of the container etc. In our approach, Δh induces a landmark $B^*\Delta h$ on the volume ΔV (see Fig. 5). The inflow, Δf , receives landmarks 0 and $f(A_{max})$ from A. Via the integration constraint, a landmark $B^*\Delta h/f(A_{max})$ is induced on duration, Δt . If and only if the duration for opening the valve, A_{max}/da , is less than this landmark, it will be considered insignificant, i.e. we can model opening the valve as a discontinuous change.

Summary

The approach to qualitative and temporal abstraction forms the basis for the automated generation of models with a granularity that satisfies the requirements on certain distinctions imposed by the respective context and task. More precisely and more modest, it provides the basis for an analysis of the feasibility and complexity of the task of automated modeling under different conditions. Even if automated modeling is not the ultimate goal, this analysis can help to formally assess the impact and correctness of certain abstractions and approximations and their underlying assumptions that are involved in hybrid modeling. This is important, because it is impossible to assess a hybrid model without relating it to a particular context. After all, there are no hybrid systems, only hybrid models...



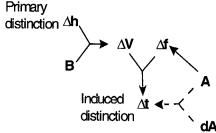


Figure 5 Opening the valve - a discontinuous change?

Acknowledgments

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References

(Iwasaki 92)

Iwasaki, Y. 1992. Reasoning with Multiple Abstraction Models. In: Faltings, B. and Struss, P. (eds), Recent Advances in Qualitative Physics. Cambridge, Mass.: MIT Press

(Struss 92)

Struss P., 1992. What's in SD? Towards a Theory of Modeling for Diagnosis. Hamscher, W., Console, L., and de Kleer, J. (eds.), Readings in Model-based Diagnosis, Morgan Kaufmann Publishers, pp. 419-450, 1992

(Struss 93)

Struss, P. 1993. On Temporal Abstraction in Qualitative Physics - A Preliminary Report. In: 7th International Workshop on Qualitative Reasoning about Physical Systems (QR'93), Orcas Island, Wa.

(Struss and Sachenbacher 99)

Struss, P. and Sachenbacher, M. 1999. Significant Distinctions only: Context-dependent Automated Qualitative Modeling. 13th International Workshop on Qualitative Reasoning and 10th International Workshop on Principles of Diagnosis, Loch Awe, Scotland, 1999