A GENERIC HARNESS FOR THE SYSTEMATIC GENERATION OF MULTIPLE MODELS

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ABSTRACT

Utilising multiple-model descriptions requires that the relationships between the various models be well-defined and can be generated systematically from a reference model. We present a generic model harness, for component-based models, that is based on a set of fundamental representational primitives that are directly related to a classification of basic model properties. This supports the customisation of the harness for a particular model and also the systematic generation of multiple models. Examples of the resulting models and their corresponding behaviours are presented for a laboratory-scale system rig.

1. Introduction

We are, at last, entering the meta-modelling stage in the development of problem solvers for engineering applications. More emphasis is beginning to be given to why we are adopting a given approach rather than how a particular approach is to be implemented. This implies a realisation that no one method, and hence a single model, is optimal for all potential applications. This viewpoint results in a methodological approach [7] to system specification in which the problem requirements are related to the characteristics of given solutions so that the selection of the 'best' approach for a given problem can be determined systematically. Further, there is a growing interest in problem solvers that utilise multiple models [2, 11, 12] to increase the generality and effectiveness of the application system. In which case the characteristics of the proposed solution need explicitly to be defined so that the relationship between the (multiple) models can be understood and hence the coherent use of these models be made.

In this paper, we propose a generalised model harness, based on the component-connection approach to modelling, such that various related models can be produced within the harness by varying basic model properties in a systematic way. We present the fundamental primitives of a generic modelling language, the CBL [1], which is clearly seen as a generalisation of classical numerical simulation languages. We then define a set of primitive model properties and the operations that vary these properties. This is supported with comprehensive simulation results with reference to an experimental system-rig, clearly showing the effect of modifying the model properties and the utility of using a generic harness for developing multiple models of continuous dynamic systems.

2. A Generalised Approach to System Modelling

Many engineering applications require a model that explicitly represents the observable (or measurable) phenomena (variables) and the sub-systems or components that interconnect them. For instance, such component models are fundamental to many model-based diagnostic approaches in that the important variables are exactly those that determine the replaceable components and hence the level of isolation and/or identification required of the diagnostic algorithm. In which case, the modelling languages adopted should therefore be based on a component-based ontology [7], assuming that a physical system can be decomposed into a set of physically identifiable components whose combined behaviour constitutes the behaviour of the overall system. Within which, a component description is given in terms of the internal mechanisms of the component such that its stimulus-response behaviour can be simulated. Component descriptions have three basic requirements: 1) to represent various physical quantities (possibly time-dependent) that are, in principle, directly observable either by humans or mechanical sensors; 2) to represent the physical quantities that form the interconnections between at least two different components; and 3) to represent relationships (possibly time-varying and/or dynamic) between observable phenomena that influence or constrain the values of the physical quantities.

On the basis of these requirements the following primitive concepts are used in such modelling languages:

- ***Structural Descriptions*** describe how a component can be decomposed into parts (or sub-components) and how these parts are interconnected. Hierarchical structures are hence supported since a part itself may have a structural model.
- ***Behavioural Descriptions*** describe the relationships between the physical quantities related to a component which may be used to simulate the behaviour of a component. This may include different modes of the behaviour of a component, e.g., the normal and faulty behaviours in diagnosis. *Representational Primitives* are used to construct the behavioural descriptions:
  - *Variables* represent physical quantities which are in general time-dependent, but may be considered constant as part of the modelling assumptions (i.e., for systems in equilibrium).
  - *Domains* are the support sets from which variables take their values at a given time, e.g., the real numbers, the set of boolean values, or other quantity spaces [10].
  - *Terminal Variables* are the subset of the variables that can be common to other components, forming the interconnections between components.
  - *Parameters* are empirical (real-valued) coefficients between variables.
  - *Relations* represent the inter-dependencies between variables and can have various representational forms, including differential equations, algebraic constraints, and sets of if-then rules.

These primitives are based on the fundamental notion of signals and system (or equivalently data and entity relationship) that governs all representational problems. Signals, here called variables, represent the object of the reasoning, i.e., the computation dependent part. Whereas the relationships describe the system, or subject, that determines how the computation will be done. Normally, this knowledge is assumed to be constant during computation. It can however be updated after computation as in machine learning or neural computing, for example.

2.1. CBL: the component based language

The potentially wide class of application areas for generalised modelling techniques require that the Component Based Language (CBL) employed within certain model-based reasoning tasks should be as general as possible. Adopting this point of view, we briefly present a description of such a language that defines a set of core concepts which is, we believe, common to all of the to the modelling of continuous dynamic systems and allows the general concepts described above to be extended by additional aspects. This allows the language to be adapted to a specified application, if necessary.

The CBL has been developed over the past ten years within a number of major European collaborative (ESPRIT) projects and used within different application tasks, including process control [7], intelligent training [5], and model-based diagnosis [4]. Unfortunately, due to the limitation on space, we cannot present the detailed syntax of the CBL in this paper. A basic outline of the syntactical structure of the language is given in figure 1 and further details can be found in [1]. Nevertheless, we hope that the way in which the CBL represents single and multiple models of physical systems will become clearer.

```
(SYSTEM        <system-name>
        {<component-instance>}
        (OBSERVABLES {<comp-name-variable-id>})
        (CONNECTIONS {<comp-name-variable-id . comp-name-variable-id>}))
```

(a) System model definition

```
(COMPONENT-CLASS   <component-class-name>
        <variable-description>
        <domain-description>
        {(MODEL <model-name>
                {<behavioural-description>})})
```

(b) Component class definition

```
(COMPONENT   <component-name>
        (IS-A <component-class-name>)
        {(MODEL <model-name>
            (WITH {<parameter-name . value>}))})
```

(c) Component instance definition

Fig. 1. Outline of the CBL Syntax

2.2. The system rig: an illustrative example

To illustrate the representation of (multiple) models of continuous dynamic systems within the framework of the CBL we utilise a laboratory-scale system rig as a test-bed shown in figure 2.

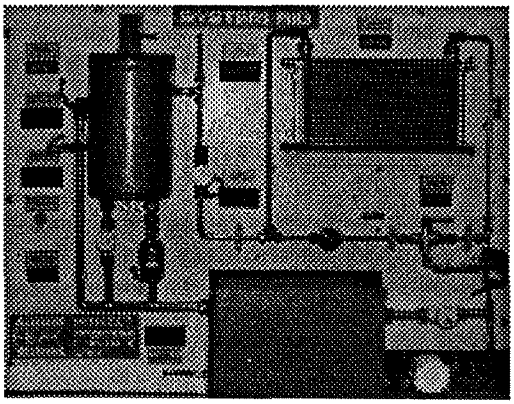

Fig. 2. The System Rig

This system is a typical representative of a wide-range class of industrial process systems and allows the behaviour of a heat exchange and extraction process to be examined experimentally. As reflected in the scanned image of this system, it consists of a number of physical components, or sub-systems, including a tank and a sump both of which store part of the fluid flowing around the system, a heater that heats the fluid in the tank, a radiator that dissipates the thermal energy of the fluid passing through it, and a pump that drives the fluid around the rig.

To exhibit the various properties or behaviours of the different models to be developed we use a numerical model of the system as the reference model. The following is the third order numerical model of the system composed of both the flow and the thermal process loops under normal (correct) working conditions [8]:

$$\dot{h} = \frac{q_i - q_o}{A}, \quad q_o = c_d \alpha \sqrt{2gh}, \quad v_2 = v_T - v_1,$$

$$\dot{T}_1 = \frac{Q + q_i e^c (T_3 - T_1)}{e^c v_1}, \quad \dot{T}_2 = \frac{q_o (T_1 - T_2)}{v_2},$$

$$T_3 = T_2 - \frac{u}{q_i e^c}(T_2 - T_a).$$

Within which, the meaning of the variables and parameters are listed in table 1. This model can be represented within the CBL as given in figure 3, where classes of components employed within the system are defined before the description of the system itself.

Variable	Variable Meaning	Parameter	Parameter Meaning
q_i	flow rate into tank	A	cross-section area of tank
q_o	flow rate out of tank	α	cross-section area of tank
h	height of fluid in tank		output
v_T	total volume of fluid	c_d	discharge coefficient of tank
v_1	volume in tank		output
v_2	volume in sump	e^c	heat-density coefficient of
Q	total heat supply by heater		fluid in tank
T_1	temperature of fluid in tank	u	radiator heat transfer
T_2	temperature of fluid in sump		coefficient
T_3	temperature of fluid exiting radiator	T_a	ambient temperature

Table. 1. Explanation of Variables and Parameters

(COMPONENT-CLASS fluid-tank

(LOCAL-VARIABLES $(f_{in}, f_{out}, f_h, v, T_{in}, T_{out}))$

(RELATED-VARIABLES $(v_{total}, v_{other}, Q_{total}))$

(DOMAIN {real} all-variables)
(MODEL correct
(BEHAVIOURAL-CONSTRAINTS

$((= (deriv\ f_h)\ (\backslash\ (-\ f_{in}\ \ f_{out})\ A)),$

$(= f_{out}\ (*\ c_d\ \alpha\ (sqr\ (*\ 2\ g\ f_h)))),$

$(= v\ (-\ v_{total}\ \ v_{other})),$

$(= (deriv\ T_{out})\ (\backslash\ (+\ Q_{total}\ \ (*\ f_{in}\ e^c\ \ (-\ T_{in}\ \ T_{out})))\ (*\ e^c\ \ v)))))))$

(COMPONENT-CLASS large-fluid-store
(LOCAL-VARIABLES $(f_{in}, f_{out}, v, T_{in}, T_{out})$*)*
(RELATED-VARIABLES (v_{total}, v_{other})*)*
(DOMAIN {real} all-variables)
(MODEL correct
(BEHAVIOURAL-CONSTRAINTS

$((= f_{out}\ \ f_{in}),$

$(= v\ (-\ v_{total}\ \ v_{other})),$

$(= (deriv\ T_{out})\ (\backslash\ (*\ f_{in}\ \ (-\ T_{in}\ \ T_{out}))\ v)))))))$

(COMPONENT-CLASS heating-element
(LOCAL-VARIABLES T*)*
(DOMAIN {real} all-variables)
(MODEL correct
(BEHAVIOURAL-CONSTRAINTS $((= T\ Q))))))$

(COMPONENT-CLASS fluid-driver
(LOCAL-VARIABLES $(f_{in}, f_{out}, T_{in}, T_{out})$*)*
(DOMAIN {real} all-variables)
(MODEL correct
(BEHAVIOURAL-CONSTRAINTS $((= f_{out}\ \ f_{in}),\ \ (= T_{out}\ \ T_{in}))))))$

(COMPONENT-CLASS heat-radiator
(LOCAL-VARIABLES $(T_{in}, T_{out}, f_{in}, f_{out})$*)*
(DOMAIN {real} all-variables)
(MODEL correct
(BEHAVIOURAL-CONSTRAINTS

$((= T_{out}\ \ (-\ T_{in}\ \ (\backslash\ (*\ u\ (-\ T_{in}\ \ T_a))\ (*\ f_{out}\ \ e^c))),$

$(= f_{out}\ \ f_{in})))))$

(SYSTEM system-rig

(COMPONENT tank
(IS-A fluid-tank)
(MODEL correct

(WITH ($(A\ .\ 15.4\times10^{-3}),\ \ (c_d\ .\ 0.6),\ \ (\alpha\ .\ 0.17\times10^{-3}),$

$(g\ .\ 9.8),\ \ (e^c\ .\ 4.18\times10^{6})))))$

(COMPONENT sump
(IS-A large-fluid-store)
(MODEL correct)

(COMPONENT radiator
(IS-A heat-radiator)
(MODEL correct

(WITH ($(u\ .\ 40),\quad (T_a\ .\ 20),\quad (e^c\ .\ 4.18\times 10^6)$*)))*

(COMPONENT heater
(IS-A heating-element
(MODEL correct)))

(COMPONENT pump
(IS-A fluid-driver)
(MODEL correct))

(OBSERVABLES ($\text{heater\_}Q_{total},\ \text{tank\_}f_{in},\ \text{tank\_}v,\ \text{sump\_}v_{Total}$*)*

(CONNECTIONS ($(\text{tank\_}f_{in}\ .\ \text{radiator\_}f_{out}),\ (\text{tank\_}f_{out}\ .\ \text{sump\_}f_{in}),$

$(\text{sump\_}f_{out}\ .\ \text{pump\_}f_{in}),\ (\text{pump\_}f_{out}\ .\ \text{radiator\_}f_{in}),$

$(\text{heater\_}Q_{total}\ .\ \text{tank\_}T_{total}),\ (\text{tank\_}v_{total}\ .\ \text{sump\_}v_{total}),$

$(\text{tank\_}v_{other}\ .\ \text{sump\_}v),\ (\text{sump\_}v_{other}\ .\ \text{tank\_}v),$

$(\text{tank\_}T_{in}\ .\ \text{radiator\_}T_{out}),\ (\text{tank\_}T_{out}\ .\ \text{sump\_}T_{in}),$

$(\text{sump\_}T_{out}\ .\ \text{pump\_}T_{in}),\ (\text{pump\_}T_{out}\ .\ \text{radiator\_}T_{in})$*)))*

Fig. 3. Numerical Model of System-Rig in CBL

Based on this model the dynamic evolution of the system can be simulated using traditional numerical integration techniques in common with the CBL description. To ease the comparison later, we herein concentrate on the exhibition of the characteristics of the two essential processes running throughout the system-rig. Figure 4 presents the (numerical) simulation plot of the flow loop and that of the temperature loop, described by the behaviour of the fluid height in the tank and the temperature of the fluid in the tank. Also shown in this figure are, (again, for the purpose of comparison to be made later) the simulation results under an assumed faulty condition where the output orifice of the tank is partially blocked.

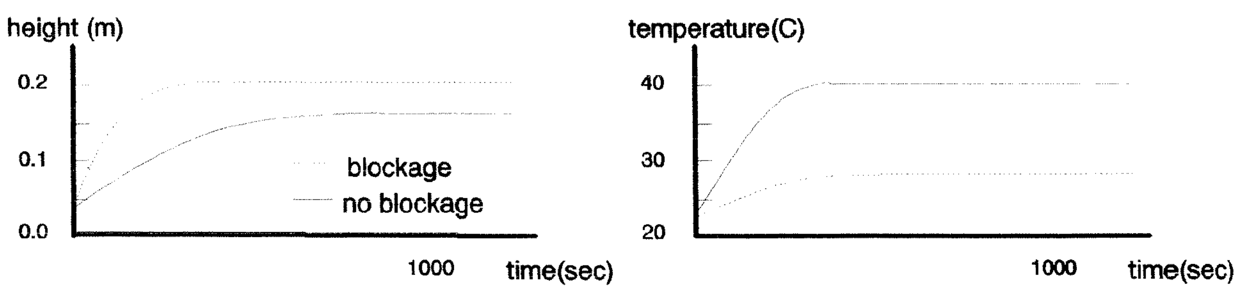

Fig. 4. Numerically Simulated Behaviours

3. Model Properties and Modelling Dimensions

As indicated in the introduction, we are interested in using the CBL as a harness from which different related models can be developed in a coherent and systematic manner by varying the fundamental model properties. The first model property in the modelling process is the choice of representational *ontology* that governs knowledge representation in general and knowledge source, knowledge level, and knowledge orientation, in particular. Within this paper, we adopt the component-based ontology to system modelling, as we are primarily interested in model-based diagnosis. Another important choice for modelling is the *scope* of the system model. It defines the physical boundary of the part of the system that is being modelled. For instance, in system engineering this property specifically determines which variables are treated as exogenous or endogenous. Having chosen the ontology and scope for the model the description of the behaviour of the system or, equivalently, the solution of a model exhibits four basic representational properties that we term *resolution*, *precision*, *accuracy*, and *uncertainty*. Resolution is a simple, but essential characteristic of system models, which denotes the number of variables used to describe the physical phenomena concerned. Precision reflects the number of distinctions supported by the description of the behaviour and the underlying semantics of such distinctions, i.e., the quantity space. Accuracy determines the closeness of the behaviour generated to that of a reference model and is clearly an important, but sometimes non-essential property for a particular task. Uncertainty describes the confidence attached to a given state or behaviour and can be used to represent the essentially subjective knowledge common in modelling real application systems.

As an example to illustrate the distinction of precision, accuracy, and uncertainty consider the case of modelling the trivial case of a single measurement, say of the temperature of the fluid in the tank of the system rig, whose true value is *100* ^oC. Figure 5 then shows different models of this value in terms of varying these properties. Figure 5(a) shows the 'true' value, whereas figure 5(b) shows a precise, real-valued, but inaccurate model. The accuracy of the model can be restored by reducing the precision! Figure 5(c) shows a (crisp) interval based model which describes the value as lying between *95--105* ^oC, which of course is correct, but less precise. In figure 5(d) a model of the same precision is used but it is now inaccurate through the process of approximation. All of the above models have assumed absolute commitment to the representation: either the true value lies inside the description or outside of it. Of course real world knowledge is not as certain as this. In which case fuzzy sets may be used to represent the inherent uncertainty. Figure 5(e) shows an uncertain, precise and correct model, using fuzzy numbers whereas figure 5(f) shows an uncertain, less precise but still accurate model.

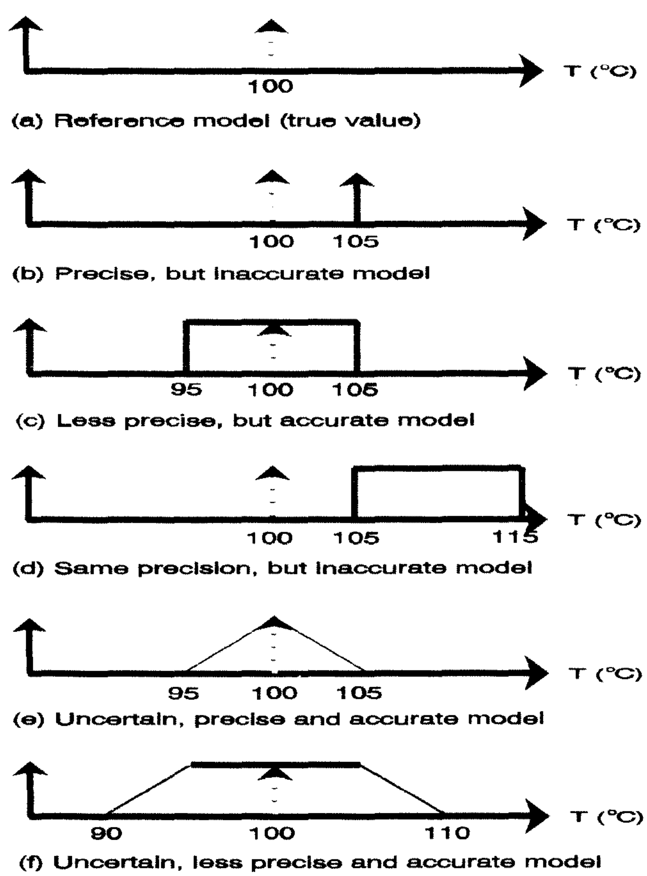

Fig. 5. Example of Model Precision, Accuracy and Uncertainty

We hope that the above discussion shows that the precision, accuracy and uncertainty are indeed distinct properties of models of system behaviour, while the scope and resolution are apparently another two basic model characteristics. Varying one of them results in a different behavioural description of the system and hence a different model is established. Following this theme, we present our view on five fundamental modelling 'dimensions' upon which to develop multiple models of a continuous dynamic system based on a common reference representation in the CBL. Application of these dimensions or model operations results in a set of related models, based on the reference model, that supports a general characterisation of multiple modelling techniques in a clear perspective. In the following, unless otherwise stated, the simulation results are obtained via the use of our Fuzzy Qualitative Simulation algorithm [9]. That is, the numerical models presented within the paper are all transformed into their corresponding (fuzzy) qualitative models. Importantly, the simulations are carried out in conjunction with a behavioural prioritiser [6] that allows the selection of the most likely behaviour out of a number of possible behaviours generated by the simulation algorithm. Also, within the results to be presented, all the lines between the qualitative states (denoted by solid circles) are given for illustrative purpose only.

3.1. Focusing models

It has been pointed out that a fundamental property of a model is its scope, which denotes the part of the physical world represented by that model. Changing a model's scope by redefining this boundary between model and environment is termed the *Focus* operation. This operation is very useful in model-based applications in general and in model-based diagnosis in particular. In which case, a model reflecting a particular focus of attention may be used to first isolate a fault to a sub-system within a plant before further focusing to a suspected faulty area or an individual component in that sub-system via focus of suspicion procedures [4, 11].

Suppose that within a model-based diagnostic process, part of the system rig consisting of the tank with the embedded heater needs to be further examined for, say, fault identification. This part of the system can then be modelled with a focused model and represented by the following CBL description of the focused 'system', with detailed definition of the components unchanged. In this case, however, the flow of the fluid in and out of the tank and the corresponding temperatures are treated as the input and output of the focused system and, therefore, assumed to be observables:

(SYSTEM focused-heating-tank

(COMPONENT tank
(IS-A fluid-tank)
(MODEL correct

(WITH $((A\ .\ 15.4 \times 10^{-3}),\quad (c_d\ .\ 0.6),\quad (\alpha\ .\ 0.17 \times 10^{-3}),$

$(g\ .\ 9.8),\quad (e^c\ .\ 4.18 \times 10^6))))$

(COMPONENT heater
(IS-A heating-element
(MODEL correct)))

(OBSERVABLES $((\text{heater\_}Q_{total}, \text{tank\_}f_{in}, \text{tank\_}f_{out}),$

$(\text{tank\_}T_{in}, \text{tank\_}T_{out}, \text{tank\_}v)))$

(CONNECTIONS $((\text{heater\_}Q_{total}\ .\ \text{tank\_}T_{total}))))$

Fig. 6. Focused Model

In order to reveal the actual behaviour under an abnormal condition modifications to this model should be made. For instance, given knowledge of a partial blockage in the output orifice of the tank an adjustment of the orifice discharge coefficient c_d to a new value is made. Both the normal and abnormal conditions are simulated and the results are provided in figure 7. Compared with those shown in figure 4, clearly, qualitative simulation outcome displays the same tendency as that in numerical simulation.

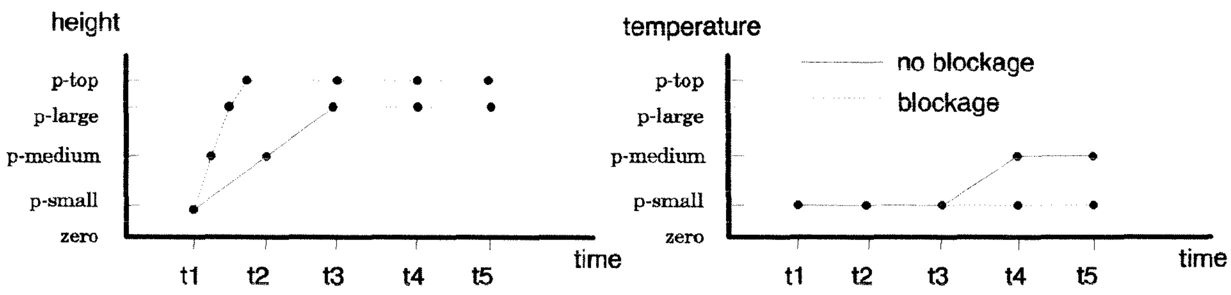

Fig. 7. Simulation Plot of Focused Models

3.2. Simplification of models

Different models of a unique system (within a given scope) can be obtained from the reference model by neglecting some of the internal variables, thereby affecting the *resolution* of the model. Such an operation on models we term *Simplification*. For example, the dynamics, or speed of response of certain variables can be assumed to be instantaneous (though known to take some finite time) with respect to the response of other variables and hence replaced by their steady state value [3]. This results in a more granular (lower resolution) model. In which case the variable may be eliminated from the simplified model.

For the system rig, when only information about the dynamics of the flow process is concerned the thermal variables can be neglected as indeed they are much slower than the dynamics of the flow loop. This leads to a simpler model with lower resolution. In terms of the CBL representation, the resulting model is presented in figure 8. Similarly, if considering the thermal process only, a simplified second-order model without flow variables can also be developed. As demonstrated in figure 9, the simplified models representing either the flow or the thermal loop only produce, again, a similar description of the evolution of the dynamics within each process to that obtained from the corresponding numerical models.

(COMPONENT-CLASS fluid-tank
(LOCAL-VARIABLES $(f_{in}, f_{out}, f_h, v)$*)*
(RELATED-VARIABLES (v_{total}, v_{other})*)*
(DOMAIN {real} all-variables)
(MODEL correct
(BEHAVIOURAL-CONSTRAINTS
$((= (deriv\ f_h)\ (\backslash\ (-\ f_{in}\ f_{out})\ A)),$
$(= f_{out}\ (*\ c_d\ \alpha\ (sqr\ (*\ 2\ g\ f_h)))),$
$(= v\ (-\ v_{total}\ v_{other}))))))$

Fig. 8. Simplified Model

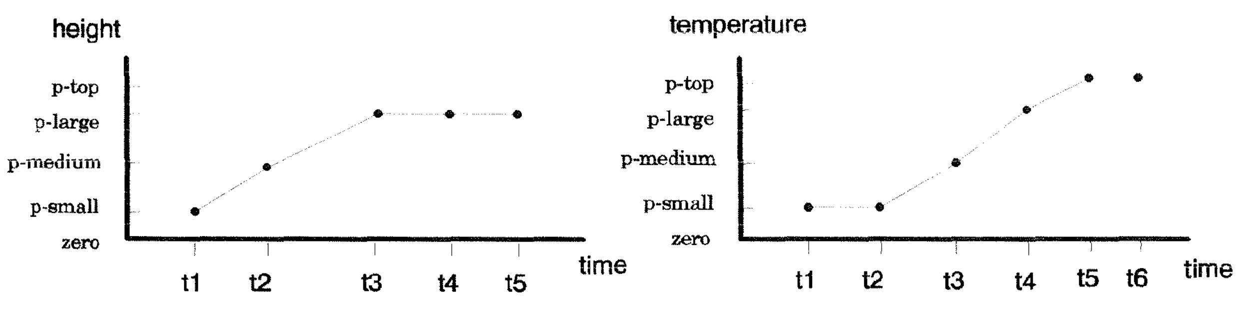

Fig. 9. Simulation Plot of Simplified Models

3.3. Abstraction of models

A very basic operation on models is *A*bstraction that modifies the *precision* of the underlying knowledge representation of the model in order to make less precise descriptions of the behaviour of the system. As such, this modelling dimension has been by far the most extensively studied within the Qualitative Reasoning community. An important and defining characteristic of *A*bstraction is that the resulting model is a 'faithful' transformation in that it will produce a behaviour that is consistent with an *A*bstraction operation applied to the behaviour of the reference model [12]. In other words, an *A*bstraction is a less precise but still correct description.

Various models of the system-rig with different levels of abstraction can be obtained in the CBL representation by varying the domain definition of each class of components such that, when using the traditional three-sign space $\{+,-,0\}$ or a space of fuzzy qualitative values {*n-top, n-large, n-medium, n-small, zero, p-small, p-medium, p-large, p-top*}, the original domain {real} in the reference model is substituted by one of them. In so doing, as an example, the component class definition of heating-elements becomes one of the two given in figure 10.

We have carried out a number of simulations using various (fuzzy) quantity spaces. In particular, figure 11 presents the behaviour generated by the utilisation of the denser quantity space given above and that produced using a quantity space consisting of (fuzzy) qualitative values that collapses the definition of the underlying semantics of *p-small* and *p-medium* into *p-small*, and *p-large* and *p-top* into *p-large*.

(COMPONENT-CLASS heating-element
(LOCAL-VARIABLES T*)*
(DOMAIN $\{+,-,0\}$ *all-variables)*
(MODEL correct
(BEHAVIOURAL-CONSTRAINTS $((=T\ Q))))$*,*

or,

(COMPONENT-CLASS heating-element
(LOCAL-VARIABLES T*)*
(DOMAIN {n-top, n-large, n-medium, n-small, zero,
p-small, p-medium, p-large, p-top} all-variables)
(MODEL correct
(BEHAVIOURAL-CONSTRAINTS $((=T\ Q))))$*,*

Fig. 10. Abstracted Models

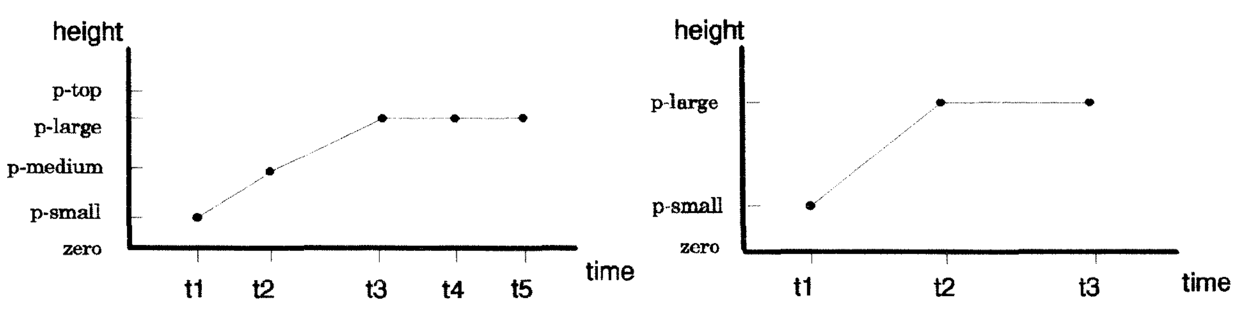

Fig. 11. Simulation Plot of Abstracted Models

3.4. Modifying commitment to models

It is clear that uncertainty can occur in two main ways within a model. The first is in the particular value to ascribe to a given measurement or observation. In particular, if there is a random element associated with the measurement, probability can be used to estimate the most likely 'next' value based on historical information. However, if the description of the measurement is inherently vague then measures based on belief or fuzzy sets can be used to capture such uncertainty. The second way that uncertainty can occur, in physical system modelling, is in the relationships between the variables, i.e. in describing the physical operations themselves. In stochastic uncertainty, Bayesian theory, or variants thereof, can be used to produce estimates of 'output' based on uncertain 'inputs' and uncertain 'operations'. Similarly, in 'fuzzy' situations possibility theory can be used to represent uncertain implications. Although uncertainty plays an important role in AI, the dimension of commitment is the least explored in Qualitative Reasoning. Most existing methods assume crisp, although abstract and possibly inaccurate models. The ability to refine uncertain measures within application systems would have important benefits for qualitative modelling applications.

As an illustration let us examine in a bit more detail the first situation that uncertainty may appear with the system-rig. For simplicity, we concentrate on the height of the fluid in the tank. Suppose that the value range of this variable in the reference model falls within *[0, 25]* (*cm*), a qualitatively precise model with full certainty may then be built upon a quantity space such as {0, (0, 10), 10, (10, 25), 25}. This is, of course, the same as the result of using abstraction. However, if knowledge of the important 'landmarks' (i.e., 10 or 25) is known vaguely an uncertain quantity space like {*zero, p-small, p-medium, p-large, p-top*} should then be adopted in order to avoid potentially important difficulties in the interpretation between behaviour derived from a model and the physical observations [10]. This results in a different model from which the crisp qualitative quantity space is used. In terms of CBL, the representation of an uncertain model is similar to the ono used to describe a crisp one, as illustrated earlier in figure 10. To visualise the implication that different degrees of commitment to a model has in the generation of system behaviour, we show the results attained by using two related quantity spaces that have the same precision but different distribution of uncertainty over individual qualitative values. As illustrated by the resulting behaviours, the modification of commitment degree leads to the change of the absolute time indices that indicate when a particular qualitative state appears. More importantly, perhaps, such modification results in a reduction of qualitative ambiguity. Indeed, although it is not reflected within the simulation plot (since we only present the most likely priority behaviour), the more committed model, with less uncertainty, generates less possible behaviours.

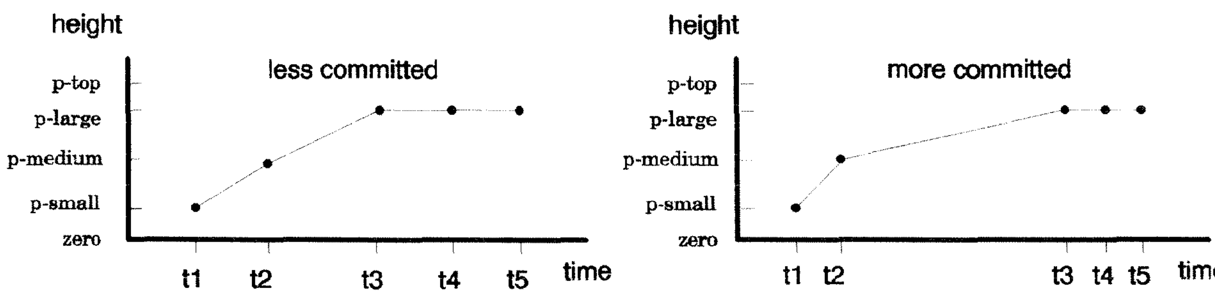

Fig. 12. Simulation Plot of Models with Different Degree of Uncertainty

3.5. Approximation of models

The last but not least operation of physical models is called *A*pproximation. This modelling dimension corresponds to the model modifications where a known functional relationship between internal variables of the model is replaced by a simpler but less accurate function. This reduction in information results in the approximate model not necessarily maintaining the correctness of the model.

Importantly, *A*pproximations need not be restricted to real-valued quantity spaces. For instance, functional relationships are represented in Fuzzy Qualitative Simulation [9] by fuzzy relations. This allows for more or less accurate descriptions through modifying the relational matrix in much the same way as linear approximations to polynomial relationships on the real-number line. In particular for the system-rig with a given quantity space, the quadratic function between the fluid height in the tank and the flow rate out of the tank may be represented by a set of if-then rules and, further, be interpreted by a look-up table through the fuzzy compositional rule of inference as given in figure 13. As such, they are, necessarily restricted to the operating range experienced during the operation or experimentation with the process, and therefore are fundamentally approximations.

(COMPONENT-CLASS fluid-tank

(LOCAL-VARIABLES $(f_{in}, f_{out}, f_h, v, T_{in}, T_{out})$*)*

(RELATED-VARIABLES $(v_{total}, v_{other}, Q_{total})$*)*

(DOMAIN {n-top, n-large, n-medium, n-small, zero,
p-small, p-medium, p-large, p-top} all-variables)
(MODEL correct
(BEHAVIOURAL-CONSTRAINTS

$$((= (deriv\ f_h)\ (\backslash\ (-\ f_{in}\ f_{out})\ A)),$$

$$(= (deriv\ T_{out})\ (\backslash\ (+\ Q_{total}\ (*\ f_{in}\ e^c\ (-\ T_{in}\ T_{out})))\ (*\ e^c\ v))),$$

$$(= v\ (-\ v_{total}\ v_{other})),$$

$$((f_{out}\ .\ f_h)\quad (n\text{-}top\ .\ n\text{-}top),\ (n\text{-}large\ .\ n\text{-}large),$$
$$(n\text{-}medium\ .\ n\text{-}medium),\ (n\text{-}small\ .\ n\text{-}small),$$
$$(zero\ .\ zero),\ (p\text{-}small\ .\ p\text{-}small),$$
$$(p\text{-}medium\ .\ p\text{-}medium),\ (p\text{-}large\ .\ p\text{-}large),$$
$$(p\text{-}top\ .\ p\text{-}top)))))$$

Fig. 13. Approximated Model

The behaviour of the system-rig, with less accuracy than the reference model, can be generated using such an approximated model. Actually, the resulting behaviour has already been presented in sections 3.2, 3.3, and 3.4 for comparison purposes. In addition, we now present the simulated behaviour from a further approximated model that represents a *medium* blockage at the output orifice of the tank. As illustrated in figure 14, such a model leads to the behaviour with highest priority representing an overflow of the fluid in the tank.

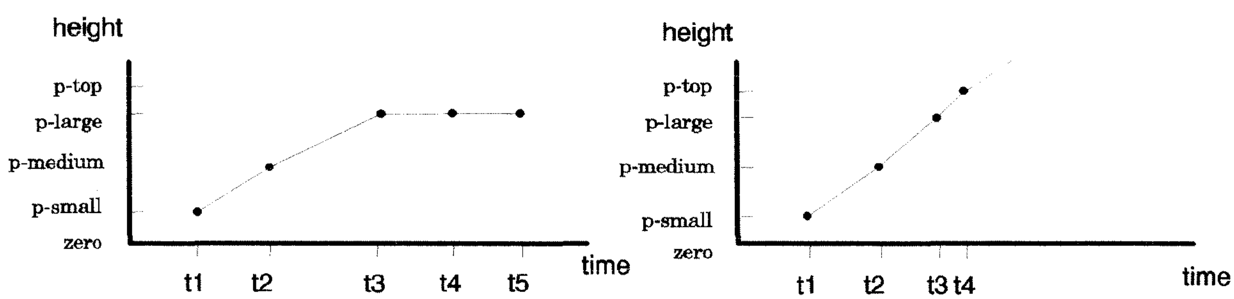

Fig. 14. Simulation Plot of Approximated Models

4. Conclusion

Although many approaches to system modelling have been developed within the last decade, in general, there does not exist a consensus on the fundamental model properties. The employment of a particular modelling technique and the use of (multiple) models requires coherent definitions of such properties and a clarification of potential modification dimensions upon which different models can be built via varying certain model characteristics. We have proposed a set of five important properties of system models and their corresponding operations and associated modelling primitives are summarised in table 2.

We have shown how these properties are related to representational primitives and that, by adopting a generic modelling harness based on these primitives, various models can be developed systematically. We believe, the resulting operations on models have a clear meaning. This allows informed decision to be made about choosing the appropriate modelling method and hence correct model(s) for a given class of problem and, also, a clearer exposition of the existing application systems that are based on the utilisation of multiple models.

Property	Scope	Resolution	Precision	Uncertainty	Accuracy
Operation	Focusing	Simplification	Abstraction	Commitment	Approximation
Primitive	Connections	Variables	Domain	Domain	Relations

Table 2. Model Properties, Operations, and Primitives

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