Qualitative Parameter Identification

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Abstract: Model identification is a core part of many automated process supervision tasks, and is conventionally achieved by estimating the parameters of a real-valued model which minimise some error function. However, the tractability of these analytic estimation methods places limitations on the nature of the process model used, such as linearity and low order. Further, the estimation algorithm has to be tuned heuristically for each application to facilitate satisfactory performance. It is argued in this article that heuristic tuning is necessary because of the inherent inaccuracy of linearised, low order, real-valued models.

This paper proposes a novel alternative parameter identification method, based on the use of fuzzy qualitative models and simulation. Fuzzy qualitative models allow imprecise and uncertain process knowledge to be explicitly represented, leading to more accurate models of ill-defined processes. The value domains underlying qualitative models mean that the parameter variations of the process model are finite, enabling a search approach to be used to identify the correct qualitative parameter values. This non-analytic approach to parameter identification removes the assumptions and limitations associated with conventional analytic parameter estimation methods. Experimental results for a 3rd order benchmark dynamic system are given.

1. Introduction

The main contribution of this paper is an investigation of how Qualitative Reasoning (QR) techniques can be used to form a novel approach to the classical control engineering task of parameter estimation. QR offers alternative methods of representation and reasoning about ill-defined dynamic systems. The aim is to create a *qualitative parameter identification* technique which removes the assumptions and limitations associated with the use of quantitative analytic process models. Such a technique would enable model-based process supervision to be applied to a larger class of real ill-defined processes.

Abe (1993) presents work on model identification based on QR methods, where QSIM (Kuipers, 86) qualitative models are identified from sequences of (symbolic) qualitative observations of state variable magnitudes. This work can be viewed as a first pass at the system identification task using qualitative methods, and as such it fails to address many issues necessary for practical application. It's use of the original QSIM representation restricts it to a purely symbolic quantity space and associated timeline, making it impractical for use with sequences of real world observations. Also, the models must be autonomous i.e. no input signals are modelled. Lichtenberg *et al.* (1994) provides a quite different qualitative model identification method, where a qualitative model in the form of a non-deterministic automaton (Lunze, 94) is derived from a series of quantised measurements of state variables of dynamic systems. This approach also has a number of restrictions regarding its practical application, such as the restriction to autonomous systems, the identification of linearised dynamic models only and the assumption that (qualitative) observations of every state variable are available.

Recent model-based diagnostic systems, MIMIC (Dvorak and Kuipers, 1989) and DYNAMO (Shen and Leitch, 1995), have performed fault identification by adapting qualitative process models until the error between the qualitative model's predicted behaviour and the process observations is minimised. Thus, at some level of description, these systems are based on qualitative model identification techniques. However, both MIMIC and DYNAMO make crucial use of domain dependent knowledge for their operation. For example, both methods require that all qualitative 'fault models' are specified a priori, and use expert knowledge in rules to relate process symptoms to the selection of candidate fault models. As such, these systems can also be considered as early work on qualitative model identification, where the requirement for domain dependent fault knowledge limits their generality.

This paper describes an approach to identifying explicitly parameterised dynamic qualitative models, where domain independent search heuristics are used to modify the qualitative parameter values until predicted behaviour matches observed process behaviour. This search-based approach is radically different to the conventional analytic parameter estimation approaches used with quantitative models. Further, the finite nature of the qualitative model's value domain enables multiple models of varying precision to be created from the given qualitative process model. These multiple models can be used as the basis of a time constrained reasoning system, which trades-off the precision of the final solution for computation time.

The next section outlines the use of quantitative parameter estimation algorithms in process supervision tasks, and argues that their limitations can be overcome by using a more appropriate model representation. Section 3 gives background on the fuzzy qualitative modelling and simulation algorithm used in this work. Section 4 describes the fundamental difference between parameter estimation of quantitative models and parameter identification in the finite space of qualitative models. The architecture developed for qualitative parameter identification is described in Section 5, and results from applying this system to a benchmark process, including the use of multiple models of varying precision, are given in Section 6. Finally, Section 7 provides conclusions about the applicability of this qualitative alternative to the task of model identification.

2. Parameter Estimation of Quantitative Models

Model identification is achieved by using an algorithm to identify an accurate model of a dynamic system from measured data. The classic approach is that of parameter estimation, where an assumed quantitative model structure (order) is specified and an algorithm is used to calculate the values of that model's parameters which minimise some error function.

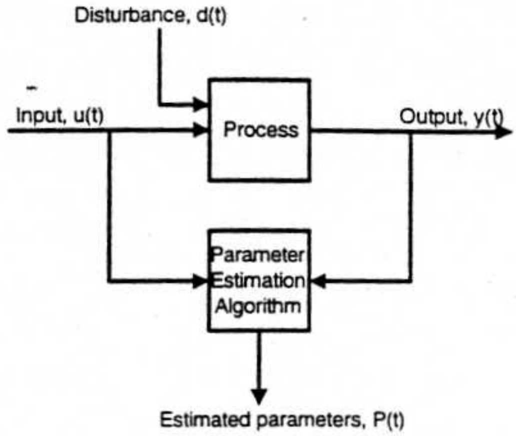

Figure 1 A typical parameter estimation scheme

A large variety of parameter estimation approaches have been proposed in the literature (Soderstrom, 1989). A typical approach is the widely used least squares method (Strejc, 80), where the parameter values of the quantitative model are calculated by minimising the sum of squared errors between the experimental data and the predictions from the model. Applications of parameter estimation methods are widespread, as in self-tuning regulators and fault detection (Isermann, 84), achieved by recursively estimating the parameters of a given quantitative process model, and detecting when these parameter values deviate from their nominal values.

Although parameter estimation algorithms and applications have been adopted successfully in many domains, it is well accepted that there are a number of restrictions and fundamental problems in their general application. A significant limitation of the majority of quantitative model parameter estimation schemes is the restriction to the use of linearised process models. This limitation is a consequence of the requirement to minimise an error function representing the difference between model predictions and measured data. The tractability of the analytical approaches to this function minimisation generally requires that the process models are linearised. Certain special classes of non-linear process models, such as the linear-in-the-parameters and bilinear structure, can be estimated analytically (Billings, 1980). However, even with these simplified classes of non-linearity, analytic estimation algorithms appear to be very difficult to implement satisfactorily.

Successful operation of quantitative parameter estimation algorithms and applications is achieved by judicious tuning of aspects of the algorithm. For example, it is necessary to provide good initial values for the parameter estimate vector and the covariance matrix, and to manage the covariance matrix throughout the execution of the algorithm to avoid poor identification and instability. Other aspects of the algorithm such as 'forgetting factors' to diminish the influence of older data are tuned heuristically by the analyst to optimise performance of the algorithm for a particular process and application. For example, in the presence of a fault, the operating point of the process may change significantly, making it all the more necessary to 'forget' older data when estimating the parameters of the new operating condition. This heuristic tuning of features of the algorithm clearly destroys the analytic properties of the approach implied by the use of quantitative analytic models.

It is argued here that these restrictions and the requirement for tuning of the algorithm arise because of the inevitable inaccuracies which exist due to the use of a finite order, linearised quantitative model to represent the behaviour of the real process. The motivation of the approach in this paper is to overcome these problems by addressing the core issue of modelling and reasoning about real dynamic processes which must be ill-defined to some degree. *It is proposed that it is better to explicitly represent this ill-defined process knowledge in the model, and to use an appropriate reasoning mechanism, than to assume an exact quantitative model and then tune aspects of the algorithm to produce satisfactory performance.* A more appropriate modelling approach will enable a wider range of real processes to be reasoned about without the need for application dependent tuning and optimisation of algorithms.

Capturing ill-defined knowledge of a dynamic process obviously requires a representation other than that of the conventional quantitative analytical model, where the underlying real number line cannot represent any uncertainty or imprecision the modeller may have about aspects of the process. The thesis here is that QR can provide the desired representation and reasoning methods for ill-defined dynamic systems.

3. Fuzzy Qualitative Reasoning about Dynamic Systems

The work presented in this paper on qualitative parameter identification builds on the work on fuzzy qualitative modelling and simulation, FuSim (Shen and Leitch, 1993), which extended the QSIM approach through the use of fuzzy sets to represent the qualitative values of parameters and variables in the model.

Similarly to the qualitative models of QSIM, the fuzzy qualitative models used by FuSim consist of two distinct parts:

Constraints (or qualitative equations); the relationships between model variables and parameters expressed in terms of qualitative equivalents of conventional differential and algebraic operators (e.g. `div`, `mult`, `add`, `sub`, `sqrt` etc.; all defined for fuzzy sets).

Fuzzy Quantity Spaces; the value domains underlying the model quantities i.e. finite sets of qualitative values (fuzzy sets defined on the real number line) from which the model's variables and parameters take their values.

Figure 2 gives a simple example of a fuzzy qualitative model of a single tank system, which shows the two and three place predicate syntax of the model constraints and gives one example of a fuzzy quantity space for the model parameter, `pipe_param`.

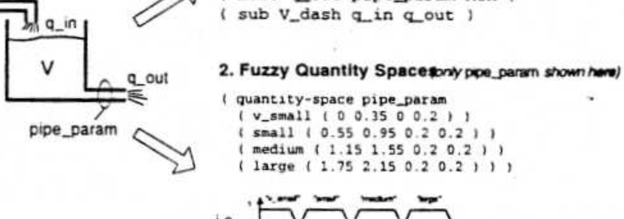

Figure 2 A Fuzzy Qualitative Model of a Single Tank

Once the system modeller has specified the model constraints, fuzzy quantity spaces for each model variable and parameter, an initial qualitative state and values of any exogenous inputs, a fuzzy qualitative simulation algorithm is applied to generate all the possible qualitative behaviours over time of that model. In this work, an enhancement of the original FuSim algorithm, Mycroft (Coghill, 1996), is used to provide the fuzzy qualitative simulator. Mycroft provides the important advantage of producing predicted qualitative states for discrete points in time, by the use of a Fuzzy Euler Integration step in the transition analysis phase of the algorithm. The output of this discrete time fuzzy qualitative simulator is a qualitative behaviour tree, containing all the possible fuzzy qualitative states consistent with the model, initial conditions, inputs and simulation algorithm. Figure 3 gives an example of the output from Mycroft, with the smaller window showing the qualitative values of each model variable in the highlighted qualitative state.

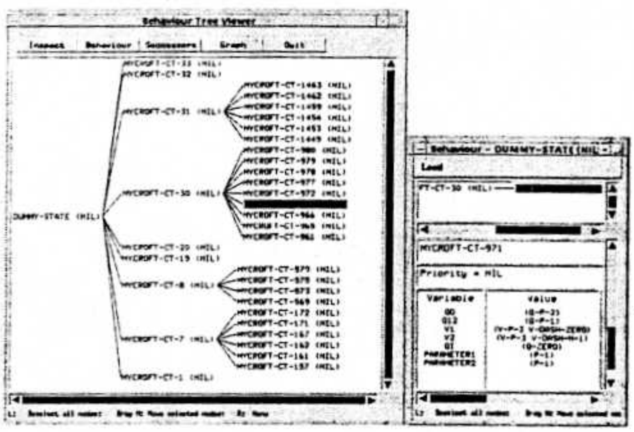

Figure 3 A Qualitative Behaviour Tree Generated by Mycroft

The qualitative behaviours produced by applying the Mycroft simulator to the fuzzy qualitative model form an exponentially growing tree of possible behaviours. This ambiguity in predicted behaviour is a natural consequence of the qualitative calculus of the model.

Thus, QR in general, and the fuzzy QR algorithms FuSim and Mycroft in particular, provide alternative modelling and reasoning methods to the conventional quantitative models and analytic methods of the control engineering domain. These alternatives provide important advantages for reasoning about processes which are incompletely known. The ability to arbitrarily define the quantity spaces of fuzzy qualitative models provides a degree of freedom to the process modeller which is simply not present in quantitative models, where the value domain is fixed as the real number line.

4. Parameter Identification of Qualitative Models

In this section, a method for the identification of qualitative model parameters is proposed which is very different to the parameter estimation techniques associated with quantitative models. The significant difference in these approaches can be explained by comparing the Parameter Spaces of qualitative and quantitative models.

The *Parameter Space*, *P*, of a model is defined here as that space generated from the Cartesian product of the value domains, *D*, of the *n* parameters of the model i.e.

$$P \equiv D_1 \times D_2 \times \ldots \times D_n$$

This represents the space all the possible assignments of parameter values which a model of a given structure can take. Thus, any parameter estimation or identification algorithm can be thought of as selecting elements from the model's Parameter Space which satisfy some prescribed criteria (e.g. minimising an error squared metric). Figure 5 presents two exemplary Parameter Spaces generated from the three parameters (*a*, *b*, *c*) of a quantitative and a qualitative model respectively :

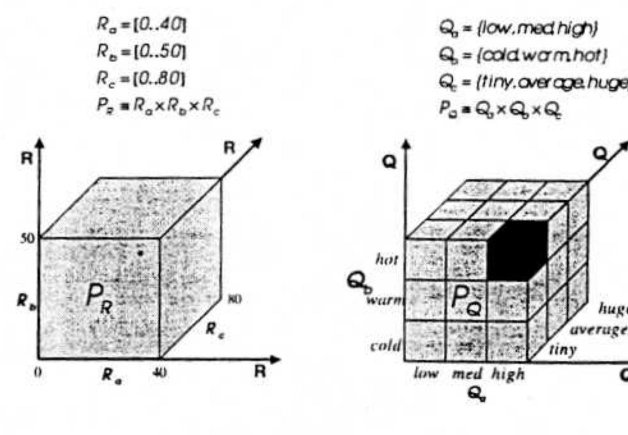

Figure 5 Parameter Spaces of Quantitative and Qualitative Models

The value domains, Q_i, underlying the parameters of a qualitative model are all finite domains. Consequently, the Parameter Space generated from these finite domains, P_Q, is also finite. This leads to the possibility of implementing a parameter identification approach using a *state-space search procedure* (Pearl, 1984) to search amongst the finite elements of the Parameter Space for those elements which satisfy the prescribed criteria. (The next section describes the matching criteria used in this approach to qualitative parameter identification). Put simply, parameter identification of qualitative models can proceed by searching for candidate parameter assignments, then testing these candidates against the prescribed criteria, and so on until all correct assignments have been identified.

In contrast, the value domains, R_i, underlying the parameters of the quantitative model are all segments of the real number line and are therefore infinitely dense domains. Consequently, the Parameter Space generated from these infinitely dense domains, P_R, is also an infinitely dense space, meaning that there exists an infinite number of possible parameter value assignments for any quantitative model. This necessitates the use of *analytic procedures* to estimate the values of model parameters which satisfy the prescribed criteria. These analytic procedures lead to the restrictions and assumptions described in Section 2, and consequently to the need for heuristic tuning of the estimation algorithm to compensate for the inaccuracy of the quantitative model.

5. QPID: An Architecture for Qualitative Parameter Identification

The QPID (Qualitative Parameter Identification for Diagnosis) system (Steele, 1996)(Steele and Leitch, 1996a) performs parameter identification of fuzzy qualitative models of dynamic systems from batches of measured data. QPID is designed to operate under a variety of user requirements typical of an industrial application such as computation time constraints, specific fault requirements and diagnostic precision. Figure 6 shows the architecture of QPID, an instantiation of the generic model-based diagnosis architecture developed for the ARTIST project (Leitch *et al.*, 1992).

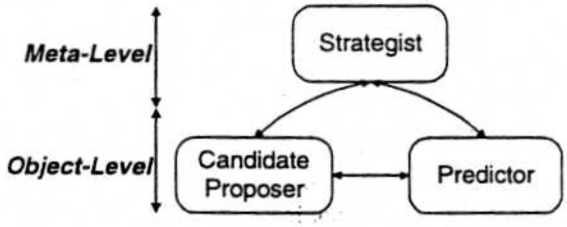

Figure 6 QPID's Meta-Level Architecture

QPID has a meta-level architecture (Jackson *et al.*, 1989), where each level is characterised by the type of knowledge used. The object-level modules reason with knowledge about the domain, in the form of a fuzzy qualitative model of the process, and it is these modules which interact to perform the qualitative parameter identification task. The meta-level module reasons with knowledge about the object-level (not the domain) to provide a control function over the object-level reasoning, ensuring that the user requirements are met.

Qualitative parameter identification involves identifying those points in the Parameter Space (P_Q) of the qualitative process model which satisfy some prescribed matching criteria. In the QPID architecture, the Candidate Proposer module is tasked with searching within the finite Parameter Space to *postulate* candidate parameter assignments which will satisfy the matching criteria. The Predictor module is tasked with *evaluating* each candidate model parameter assignment to decide whether it satisfies the matching criteria.

5.1 The Predictor

The matching criteria used in QPID, as in any other model identification method, requires comparison of the candidate model's predicted behaviour with the batch of observed process behaviour. The Mycroft fuzzy qualitative simulator (Coghill, 1996) is used in the Predictor to generate predicted behaviour from the fuzzy qualitative process model. Its use of a Fuzzy Euler Integration step results in fuzzy qualitative predictions at discrete points in time. This eases the comparison of qualitative model predictions to the batch of measured data, which also consists of values observed at discrete timepoints.

The use of a qualitative model and simulation algorithm raises interesting issues regarding the process model's evaluation against real world data. In general, models can be considered as being instantiations of theories, which are open to refutation or validation with respect to the facts in their domain of application. In the case of predictive models, if the model's predicted behaviour is shown to be consistent with the facts (i.e. the observations) then the model is validated. Conversely, if the behaviour is inconsistent with the observations then the model is refuted. This is the essence of the evaluation task of the Predictor - each candidate model must be refuted or validated with respect to the observations obtained from the process. However, due to inherent ambiguities of the model's qualitative calculus, the output from the Mycroft simulation algorithm is an exponentially growing tree of predicted qualitative behaviours, each branch representing a possible behaviour of the model. How do these non-unique predicted behaviours affect the evaluation of the models ? It follows from the nature of the evaluation decision described above, that to refute such a model would require that each and every branch of the qualitative behaviour tree is shown to be inconsistent with the observations. Consequently, it follows that to validate such a model requires only that one of the predicted behaviours is shown to be consistent with the observations.

These conditions for refutation and validation have a major implication for the way in which qualitative behaviour trees are elicited from candidate models in the Predictor. Clearly, there is no need to generate and maintain the entire qualitative behaviour tree of a candidate model - all that is necessary to facilitate the evaluation of a candidate qualitative model is that predicted states which are consistent (matching) with the observations are maintained in the behaviour tree. When consistent predicted states can be found along one behaviour branch up to the last of the sequence of relevant observations, the model can be validated. When there are no longer any unexpanded consistent states in the tree, the model can be refuted. This naturally leads to an evaluation algorithm which interleaves prediction with comparison to the observations - all predictions which are inconsistent are eliminated from the behaviour tree, with the result that only the 'matching behaviour tree' is created. Maintaining only this sub-tree helps to ease the amount of branching in the qualitative simulation, although the problem does remain inherently exponential. Figure 7 gives a schematic illustration of how the matching behaviour tree is maintained during evaluation of a candidate model.

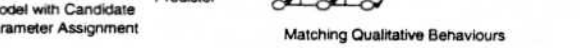

Figure 7 Evaluating Models in the Predictor by Matching Qualitative Behaviours to Process Data

5.2 The Candidate Proposer

The Candidate Proposer module uses two domain independent search heuristics to guide the selection of the candidate parameter assignment from the Parameter Space.

The first search heuristic is based on the knowledge of causality which is present in the fuzzy qualitative models. The constructive nature of the qualitative simulation algorithm used requires that the modeller specifies a model with a definite causal order to the constraints. From such models it is possible to find which parameters have a causal influence on which variables, and what the sign of that influence is, creating a causal graph. Information from the Predictor about the discrepancies between predicted and observed values of variables is then used with the causal graph to identify those parameters which could be responsible for the discrepancies. The qualitative values of the next candidate model's parameters are then shifted so as to reduce the discrepancy.

The second search heuristic is based on the empirical observation that correct qualitative models tend to form 'clusters' in the Parameter Space. (Due to inherent ambiguities in qualitative simulation, generally more than one point in the Parameter Space will form a correct candidate model). This observation is exploited in the Candidate Proposer by using a heuristic which prefers the neighbouring values of any previously found correct parameter assignments.

In summary, performing parameter identification of qualitative models involves searching in the finite Parameter Space generated by the quantity spaces of the model parameters. The goal test of this search is whether the predicted behaviour of the qualitative model with the candidate parameter assignment matches the observed behaviour of the physical system. The 'postulate and evaluate' cycle of searching for and then testing parameter assignments is realised by the Candidate Proposer and Predictor modules respectively, as shown in figure 8.

Figure 8 The Postulate/Evaluate Cycle to Perform Qualitative Parameter Identification

5.3 The Strategist

The remaining module of QPID, the Strategist, is the meta-level module tasked with controlling the object-level such that the user requirements, particularly time constraints, are satisfied.

Model-based reasoning in general, and qualitative simulation in particular, is a computationally expensive task. The repeated use of the fuzzy qualitative simulation algorithm in the Predictor to evaluate the various candidate parameter assignments postulated by the Candidate Proposer means that QPID's object-level reasoning can indeed require large amounts of computation. This is problematic for a time constrained reasoning system such as QPID. Lesser *et al.* (1988) address this issue and describe an *Approximate Processing* approach to real-time search-based problem solving. They state that if a problem solver's estimate of when the optimal solution will be formed exceeds the available time resource, the system should perform Approximate Processing that trades off the quality of the final solution against the computation time required to derive it (where the dimensions of solution quality are domain specific).

(Steele and Leitch, 96b) describes how the Strategist of QPID can vary aspects of both the representation and the reasoning of the object-level, forming an Approximate Processing approach which ensures that a solution is produced within a time constraint. Briefly, the Strategist uses a hierarchy of multiple qualitative models of the process of varying *precision* - defined in (Leitch and Shen, 94) as the number of distinctions in the value domains of the model - and selects the most precise model which will lead to a solution within the prescribed time constraint. The Strategist can also, if necessary, vary the *completeness* of the qualitative simulation algorithm i.e. the algorithm can be altered so as to generate only a subset of the possible behaviours of the current model. This reduces the computation time required to evaluate candidate models, but at the expense of guaranteeing that all correct qualitative parameter assignments will be identified.

6. Experimentation

This section presents results of performing qualitative parameter identification on a benchmark dynamic system. The previous sections have described how the modelling and reasoning procedures used in the qualitative approach are radically different to those of the conventional quantitative methods such as linear least squares. Indeed, it has been argued that the two approaches could not be considered to be equally applicable to any given problem - if accurate, precise and certain domain knowledge exists, then conventional quantitative approaches would be used. On the other hand, the proposed qualitative approach would be used in the case of ill-defined domains, where process models must represent imprecise and uncertain knowledge. As such, this section does not give a direct comparison of the two approaches to model identification, but rather reports results typical of the developed qualitative approach.

6.1 Experimental Setup

The dynamic system chosen to demonstrate the application of QPID is the benchmark three coupled tanks process, as shown figuratively in figure 9.

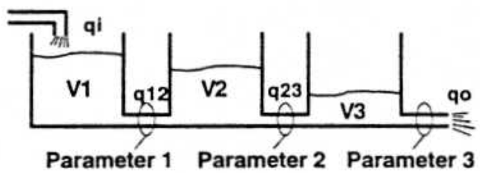

Figure 9 Three Coupled Tanks

To ease the initial testing of QPID, the process is itself simulated in software using the Runge-Kutta simulator provided by the SIMULINK toolbox of MATLAB. This facilitates quick and easy simulation of different fault scenarios, which are used to generate batches of process data for qualitative parameter identification in QPID. A dynamic, third order, non-linear numerical flow model is used to provide the behaviour of the tanks process. The QPID system itself is implemented in LISP, using the Harlequin LispWorks3.1 environment, running on a DEC Alpha workstation.

6.2 The Fuzzy Qualitative Model of the Three Tanks System

Fuzzy qualitative models consist of two parts: constraints and fuzzy quantity spaces. The process modeller must provide both of these, appropriate to the domain knowledge and the task to be performed (e.g. fault detection).

Constraints

To provide a behavioural model of the process in terms of qualitative equations relating various quantities, it is assumed the modeller has some knowledge of the internal structure of the process, in particular which quantities are the state variables. Even in the case of ill-defined domains like chemical and biological processes, knowledge of the causal structure still commonly exists. Of course, there may be great uncertainty and imprecision about the accurate values of the parameters in this model structure.

For the three coupled tanks, a third order non-linear model structure was assumed and used to create the fuzzy qualitative model given in figure 10.

```
( sub AUX1 V1 V2 )
( sqrt AUX2 AUX1 )
( mult q12 parameter1 AUX2 )
( sub V1-dash qi q12 )

( sub AUX3 V2 V3 )
( sqrt AUX4 AUX3 )
( mult q23 parameter2 AUX4)
( sub V2-dash q12 q23 )

( sqrt AUX5 V3 )
( mult qo parameter3 AUX5 )
( sub V3-dash q23 qo )
```

Figure 10 Fuzzy Qualitative Model Equations for Three Tanks Example

The equations are structured such that there are three qualitative parameters in the model (`parameter1`, `parameter2`, `parameter3`), one in each pipe flow equation. QPID will identify the qualitative values of these parameters. These lumped parameters are coefficients whose value can be directly related to physical characteristics of the plant such as the effective cross sectional area of the outflow pipes and the pipe discharge coefficient, which is necessary for the particular task of fault diagnosis. A different model structure, with a different parameterisation, may be appropriate for other model-based reasoning tasks.

Fuzzy Quantity Spaces

The modeller must then specify the subjectively important qualitative values which each model parameter and variable can take. The required precision of the parameters' quantity spaces depends on the task which the identified parameters will be used in. For example, in the case where QPID is coupled to a diagnostic agent, the quantity spaces should only be as precise as necessary to produce a fault diagnosis. There is little point in specifying a quantity space consisting of, say, one hundred qualitative values, as this is likely to be overly detailed and reduces the cognitive efficiency of QPID.

From the physical dimensions of the plant, it is known that the parameter values of interest would span the numerical range from 0.00 (representing full pipe blockage) to around 2.30 (clear pipe cross section, maximum discharge coefficient). In this example, 8 qualitative values were defined for this most precise quantity space of the parameters. This arbitrary number of qualitative values was appropriate to describe the varying degrees of pipe blockage for a fault diagnosis application. Each qualitative value has an associated linguistic label, *p_1* through *p_8*. The variables of the model were each given quantity spaces consisting of 16 qualitative values. Figure 11 graphically shows the fuzzy quantity spaces defined for the three parameters (`parameter1`, `parameter2`, `parameter3`), the volume variable (`V`), volume rate-of-change (`V-dash`) and the flow variables (`qi`, `q12`, `q23`, `qo`).

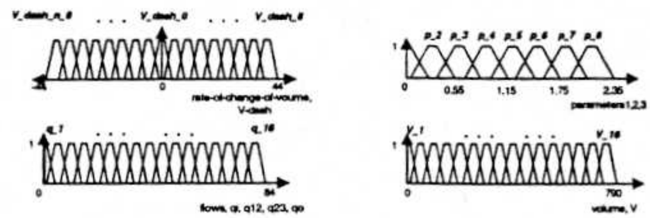

Figure 11 Fuzzy Quantity Spaces for Three Coupled Tanks Model

QPID can now be used to identify the parameters of the above fuzzy qualitative model, by searching within the Parameter Space of the model for those parameter assignments which are validated as correct against a batch of process data. Figure 12 shows the Parameter Space of this model - as each of the three parameters can take 8 possible qualitative values, the Parameter Space consists of 8x8x8=512 elements.

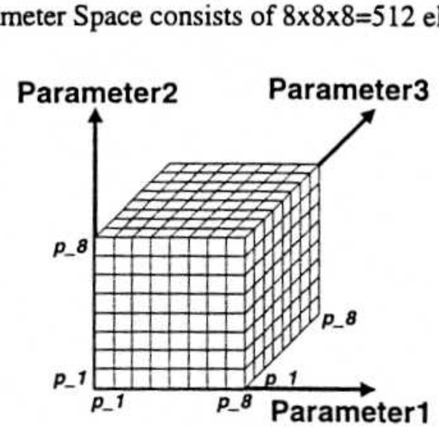

Figure 12 The Parameter Space of the Three Coupled Tanks Model

6.3 Results from QPID

A batch of process data describing the faulty behaviour of the plant with a large blockage in the second pipe was used in this first experiment. QPID was used to identify the parameter values of the above fuzzy qualitative model from this batch of data. The results of this qualitative parameter identification are presented graphically in figure 13. The elements of the Parameter Space which were identified as correct parameter assignments are shown shaded. The elements corresponding to incorrect parameter assignments are left blank.

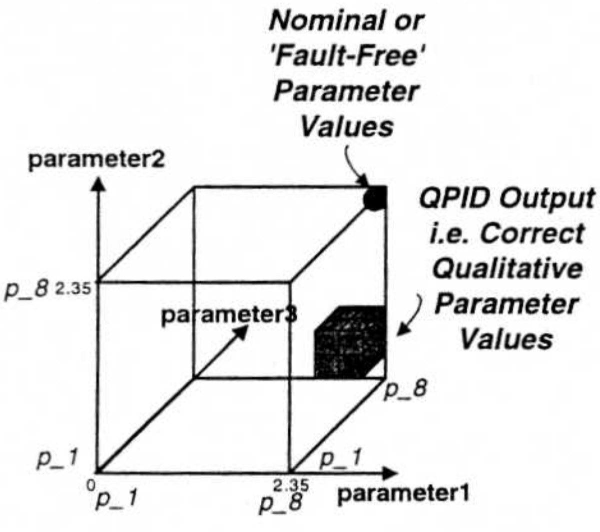

Figure 13 Identified Qualitative Parameter Values

Obviously, solutions obtained from QPID are not unique i.e. more than one set of parameter values results in a correct qualitative model. In this example, 8 of 512 elements of the model's Parameter Space were evaluated as correct. This is due to the well known ambiguities of qualitative simulation - more than one candidate qualitative model may produce a behaviour tree which contains a behaviour which matches the batch of observations of the process. This ambiguity in the identified parameter values has to be accepted as part of the paradigm shift from quantitative to qualitative methods. For some process supervision tasks, it is not a significant problem. For example, consider the task of fault detection, where the process operator knows that the fault-free process has nominal parameters which take the maximum qualitative values (no blockages, thus maximum cross-sectional areas of pipes). The correct values identified from QPID in this experiment are clearly all very different from the nominal values. In particular, the value of `parameter2` has decreased significantly, indicating that a large blockage has occurred in the second pipe. Thus, even though the identified parameters are ambiguous, there is sufficient information to detect a fault and to identify the approximate size of the blockage. Certainly, the large number of elements in the Parameter Space evaluated as incorrect parameter assignments could be sufficient to reassure the process operator that the process has not entered a safety critical operating region.

6.4 QPID Using Multiple Models of Varying Precision

Section 5.3 outlined how the Strategist of QPID can vary the representation of the model used at the object-level of QPID to ensure that a solution is available within the prescribed time constraint. In particular, the Strategist selects from multiple models of the process the one of the highest precision which will lead to a solution in the available time. Reasoning about the selection of the most appropriate model precision for the current time constraint requires that the multiple models of the process be related and ordered in some formal way. In QPID, the models are stored in a hierarchical scheme, with each level of the *Precision Hierarchy* consisting of a fuzzy qualitative model of a certain precision, as shown in figure 14.

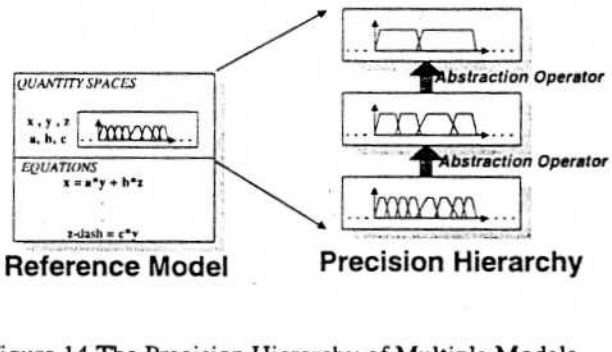

Figure 14 The Precision Hierarchy of Multiple Models Used in QPID

The highest precision, or reference, model is that which encapsulates the best knowledge of the modeller i.e. the most precise and least uncertain model. The less precise models at the upper levels of the hierarchy are generated by applying an *abstraction operator*. This operation involves collapsing together certain neighbouring qualitative values (fuzzy numbers) in the quantity spaces of the precise models to form the qualitative values at the lower levels of precision. (Note that the constraints of the qualitative models remain unchanged across the levels of the Precision Hierarchy - only the value domains change).

From the definition of the three tanks reference model used in the previous experiment, the abstraction operator can then be applied to create the models at the other levels of the Precision Hierarchy. Figure 15 shows the results of applying the abstraction operator to quantity spaces of the reference model (for brevity, only the parameter and volume quantity spaces are shown). Also shown are the corresponding Parameter Spaces generated by the models at each level of the hierarchy. Importantly, the size of each Parameter Space varies polynomially with the precision of the model - thus, it requires far less computational effort for QPID to identify the qualitative parameters of a low precision model.

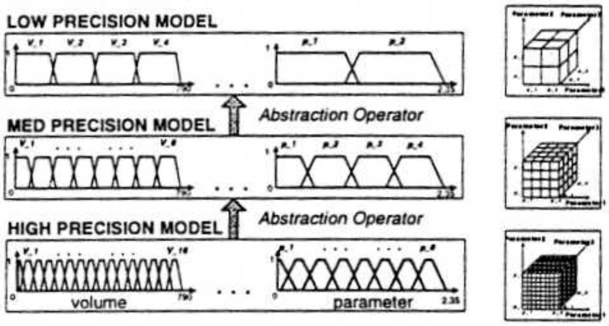

Figure 15 Precision Hierarchy and Parameter Spaces for Three Tanks Example

To demonstrate the use of QPID with multiple models of varying precision, the first experiment was repeated with each model from the above Precision Hierarchy. The results are shown in the same graphical format in figure 16, and table 1 contains the computation times (in CPU seconds) required to perform exhaustive parameter identification of the three models.

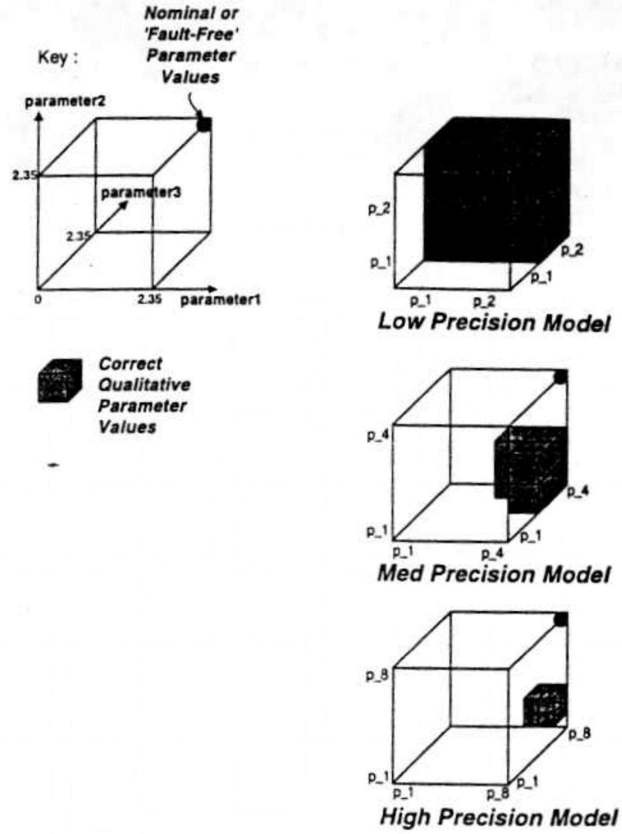

Figure 16 Identified Qualitative Parameter Values

Level of Hierarchy	Computation Time (CPU secs)
Low Precision	4.2
Med Precision	29.1
High Precision	53.0

Table 1 Computation Times at Each Level of Hierarchy

These results show that the ambiguity in the results are more problematic when using less precise models e.g. using the least precise qualitative model, 4 out of 8 elements in the Parameter Space were evaluated as correct parameter assignments, including the maximum qualitative assignment corresponding to the nominal process parameter values. Thus, in a fault detection task, the process operator would not be aware of the presence of the blockage fault from these imprecise results alone. However, they could be assured that the process had not entered the operating region of the parameters which were identified as incorrect. The medium precision model has 6 out of 64 correct parameter assignments, providing better information to the operator, and clearly shows that `parameter2` has shifted from its nominal value. Finally, as before, the high precision model isolates an even smaller correct subspace, indicating a substantial blockage in the second pipe.

As expected, the computation times required to perform exhaustive parameter identification of each model at the three levels of the Precision Hierarchy are significantly different. This is primarily due to the polynomial increase in the size of the Parameter Spaces generated by the models of the Precision Hierarchy, as shown in figure 15. (N.B. Incorrect models are evaluated more quickly than correct models, as less matching qualitative behaviours have to be maintained - this is why there is less of a computation time increase between the med and high levels of precision). These results demonstrate how an aspect of solution quality (i.e. precision) can be traded-off for computation time. (Steele and Leitch, 96b) gives more detail on how this can be used in QPID as the basis for time constrained model-based diagnosis.

7. Conclusions

The QPID system uses fuzzy qualitative modelling and simulation techniques to form the basis of a novel approach to parameter identification of dynamic systems. The use of these qualitative methods

- is more appropriate for modelling and reasoning about ill-defined processes
- leads to a state-space search approach to parameter identification
- allows multiple models of varying precision to be used as the basis of a time constrained reasoning system.

It has been argued that the limitations and heuristic tuning associated with conventional quantitative parameter estimation methods arise due to the use of a real-valued model to represent the incompletely known real process. Fuzzy qualitative models obviate these problems by explicitly representing uncertain and imprecise process knowledge in the model. The difficulty in reasoning with these models, however, is that the qualitative calculus leads to multiple predicted behaviours and ambiguous results. Multiple models of varying precision can be used to control the computation time required, but at the expense of increased ambiguity and imprecision in the results.

The qualitative parameter identification method presented here is essentially a simple concept - search within the finite space of model variations for all models which are consistent with process observations. However, this identification method requires a significant paradigm shift from the analytic method of calculating the parameters of a real-valued model which minimise some error function. This paper has exposed some of the issues and problems associated with the use of qualitative methods. Armed with such knowledge, the analyst is better placed to know when it is appropriate to make this shift from quantitative to qualitative techniques for model identification.

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