Integrating Qualitative Simulation for Numerical Data Fusion Methods

Yang Gao and Hugh F. Durrant-Whyte
Department of Engineering Science
University of Oxford
Oxford OX1 3PJ, UK
yang@robots.oxford.ac.uk and hugh@robots.oxford.ac.uk

Abstract

Work described in this paper is aimed at developing a monitoring and fault detection system for the process plant. In particular this work concentrates on how to combine qualitative reasoning techniques with conventional numerical sensor fusion techniques. The advantages and disadvantages of using pure numerical or pure qualitative technique alone are first demonstrated. A method of developing a combined semi-quantitative model is then introduced. A number of algorithms are designed to analyse semi-quantitative predictions information. Finally, the semi-quantitative model is used to perform the system monitoring and change detection. The application of the algorithms developed is demonstrated by a number of examples throughout the paper, based on real data.

1 Introduction

Work described in this paper is aimed at developing a monitoring and fault detection system for a process plant. In particular this work concentrates on how to combine qualitative reasoning techniques with conventional numerical sensor fusion techniques.

Qualitative physics provides an account of behaviour in the physical world. The vision of qualitative physics, in conjunction with conventional physics, is to provide a much broader formal account of behaviour, an account rich enough to enable intelligent systems to reason effectively about the real world. Qualitative physics predicts and explains behaviour in qualitative terms. In contrast with qualitative techniques, numerical data fusion methods described physical system in more accurate numerical terms. Most sensor based systems employ a large variety of sensors to obtain information. How the information obtained from different sensing devices is combined to form a description of the system is the sensor fusion problem. A number of sensor fusion methods have been developed, ranging from simple least-squares fitting algorithms to complex statistical inference methods. These algorithms provide statistical descriptions of system behaviour based on statistical uncertainties involved. However, qualitative reasoning methods provide features which are difficult to capture using pure numerical methods. It functions with incomplete knowledge, a qualitative analysis does not require a detailed quantitative model or complete data on the system which may be difficult to obtain; A qualitative model may represent a class of numerical models, because different numerical models can corresponding to the same abstract qualitative model; this is in contrast to the complete problem specific type of a numerical model. Qualitative analysis provides direct, often causal explanations between different variables.

If the information available about a system is purely qualitative, then the qualitative methods will be used; when precise numerical information is available, then a number of numerical methods can be utilised. However, in many situations, where numerical information is substantial but stochastically imprecise, the predictions made are more confident than using the purely qualitative ones. The qualitative predictions on the other hand provide causal explanations. In such cases, using a combined method may take advantage of both techniques and avoid the weakness of using one alone. The work described in this paper is an example of this case.

In this paper, we focus on general physics of a system. The idea behind integrating the two techniques is also to get some qualitative knowledge of the process and sensor physics and incorporate them into the numerical data fusion processes. The application of the algorithms developed is demonstrated by a number of examples throughout the paper, based on a real system, process plant.

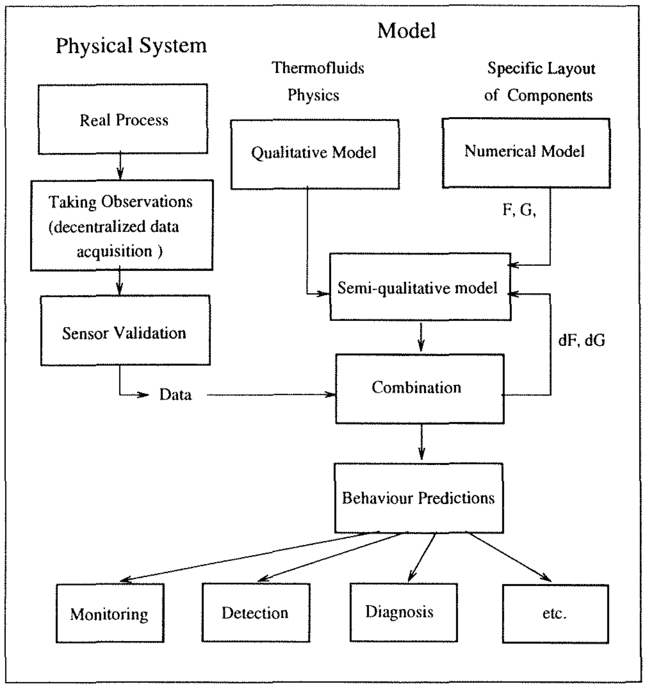


Figure 1: Outline of System

The structure of this system is outlined in Figure 1. We first introduce a method of building a qualitative physical model to simulate the system behaviours. We then develop the system model using a classical state-space description, and explain problems associated with parameter uncertainty. Finally we discuss the common theme that lies between them and the model generated using the combined knowledge. The system state estimate and behaviour prediction generated by this combined model, which we term it as semi-quantitative model, are analysed for the purpose of system monitoring and fault detection.

2 System Modelling

The process plant dynamic system is loosely modelled around a conventional nuclear power plant. It incorporates four pumps, three boilers, two heat exchangers and fifty six computer controlled valves. The sensing level provides large quantity of redundant sensor information collected from more than two hundred sensors (thermocouples, flow meters and pressure sensors) which are distributed at appropriate locations in the plant. Details of the process plant system and sensing system can be found in [11].

We consider the simple case for the process plant system. The circuit incorporates one boiler, one pump and one heat-exchanger. For reasons of simplicity, we assume all the valves along the circuit are in the "open" positions and that there is no energy loss in pipes and pumps. Only temperatures from the input and output of the boiler are to be measured and predicted. We start by switching on all three components. When the temperature of the output of the boiler reaches a certain point, the second pump which is in parallel with the first one will be switched on. What happens next?

To answer this question, we have modelled the system both qualitatively and numerically.

2.1 Qualitative Model

The qualitative model of the example discussed above is developed based on the principle of energy conservation in thermodynamics:

$$Q_{in} = C_b \dot{m}(T_{out} - T_{in}) \quad (1)$$

$$Q_{out} = UA(\frac{T_{in} + T_{out}}{2} - T_{air}) \quad (2)$$

$$Q_{out} = C_f \dot{m}(T_{out} - T_{in}) \quad (3)$$

$$Q_{in} - Q_{out} = Q_{net} \quad (4)$$

$$d\dot{T}_{out}/dt = Q_{net} \quad (5)$$

where Q_{in} and Q_{out} are the heating input and heating output, T_{in} and T_{out} are the temperature input and output from the boiler, T_{air} is the plant room temperature, $\dot{m}$ is the mass flow, C_b and C_f are the specific heat for boiler and heat exchanger, U is the heat transfer coefficient for convection loss, and A is the heat transfer area. In qualitative modelling, these system parameters are defined using qualitative ranges and landmark values as follows: the heat input is a value $Q_{in}*$ which lies in the range $(0, \infty)$, mass flow has two values when working with one pump or two pumps respectively: denoted as mf and $2mf$. The rest of the parameters are similarly defined. One particular landmark value is setup for the temperature output from the boiler, T_{hot}. This landmark is set only for the purpose of deciding the time point at which to switch on the second pump, that is when $Tout$ is higher than that of $Thot$ and increasing, then the second pump is switched on.

The above model provides a qualitative description of the structure of the mechanism and an initial qualitative state without knowing the exact values of the landmarks. The qualitative simulation package (QSIM) is used here to provide automatic generation of the qualitative behaviours of the state variable. The behaviour predictions generated by the above qualitative model are shown in Figure2 and Figure 3. The

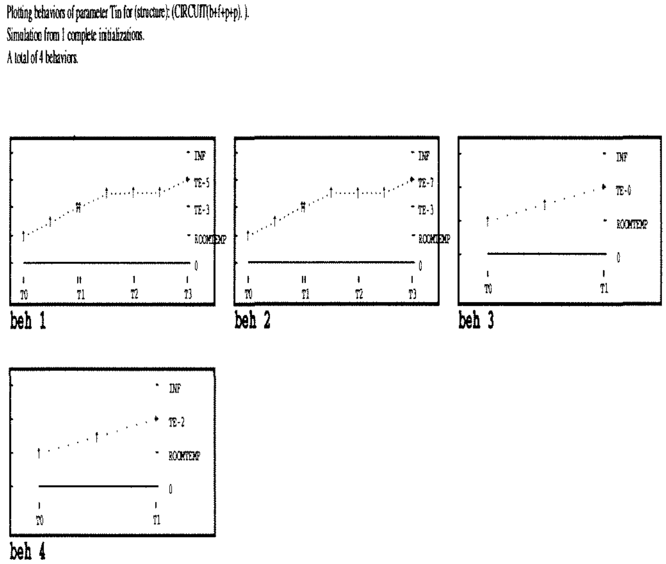


Figure 2: QSIM plot of temperature input of one to two pumps running.

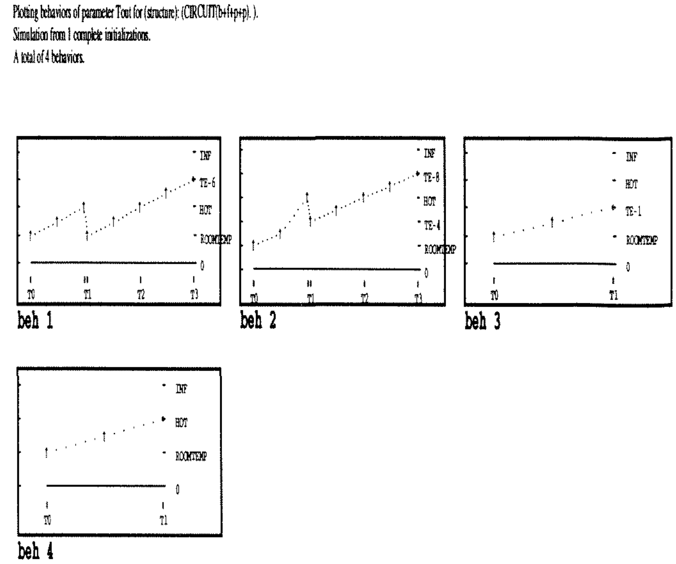


Figure 3: QSIM plot of temperature output of one to two pumps running.

corresponding changes in mass flow are shown in Figure 4.

2.2 Discussion

From Figure 2, Figure 3 and Figure 4 we can see that qualitative model predictions include all the possible behaviours that can be deduced from the given qualitative information. Behaviour 1 indicates the case that when the second pump is switched on, $Tout$ drops back to room temperature then increases again; behaviour 2 indicates $Tout$ drops to a temperature point which is between room temperature and $Thot$. Behaviour 3 and 4 show the cases which the state transition conditions ($Tout \gg Thot$ and $Tout$ is increasing) are not met, so $Tout$ is either steady at $Thot$ (beh4), or below $Thot$ (beh3), the second pump is not switched on at all, see beh3 and beh4 in Figure 4.

Qualitative predictions may also contain spurious behaviours that do not reflect any real situation. For example, behaviour 1 shown above, $Tout$ can not drop back to room temperature when Tin is higher than room temperature. In a real case we can always guarantee that the transition conditions are satisfied, so only behaviour 2 is the correct answer, although beh3 and beh4 are logically correct.

2.3 Numerical Modelling Using State-Space Description

The system we consider is assumed to be a first order system following [12], where the physical differential equation of steady flow processes can be described as a linear lumped-parameter differential equation. A recursive least-square parameter estimator is used to process the sensor data and find the parameters for the state transition matrix and the input gain matrix.

Using a lumped-parameter system, the discretised state transition equation is of the following form:

$$\mathbf{x}(k+1) = \mathbf{F}\mathbf{x}(k) + \mathbf{G}\mathbf{u}(k) + \mathbf{v}(k), \qquad (6)$$

where $\mathbf{x}$ is the vector of temperature (input and output from the boiler in our example), $\mathbf{F}$ is the state transition matrix, $\mathbf{G}$ is the input gain matrix, $\mathbf{u}$ is the input vector (heat inputs) and $\mathbf{v}(k) \sim \mathcal{N}(\mathbf{0}, \mathbf{Q}(k))$ is the process noise.

Equation (6) can also be written as the following:

$$\begin{bmatrix} T_{out}(k+1) \\ T_{in}(k+1) \end{bmatrix} \qquad (7)$$

$$= \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} T_{out}(k) \\ T_{in}(k) \end{bmatrix} + \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} [T_{air}(k)] + v(k)$$

In the system we are considering, all the temperatures are measurable; the determination of the parameters for this model is from experimental data obtained from the process plant. Real measurement data of the temperature input and output from the boiler is shown in Figure 5(a). The corresponding changes in flow cross the boiler are shown in Figure 5(b).

The system model is obtained using least squares

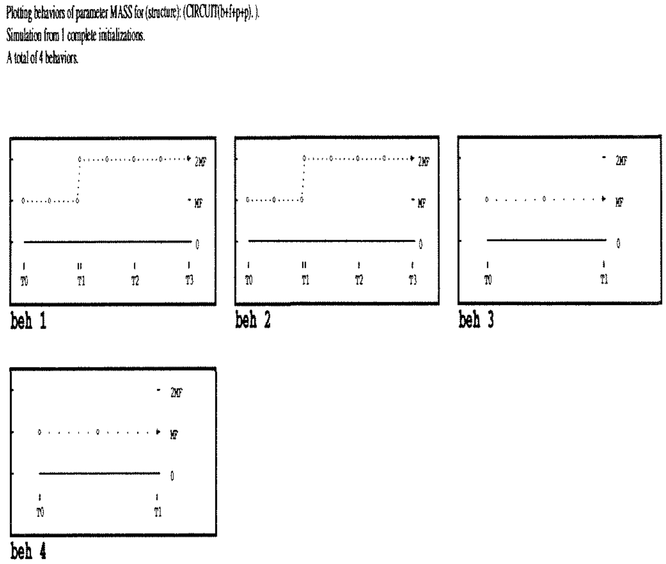


Figure 4: QSIM plot of mass flow changes with one to two pumps running.

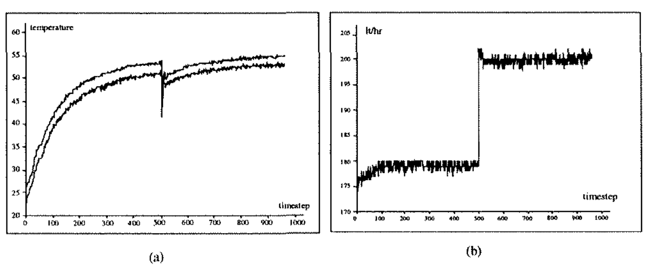


Figure 5: (a)Temperature data with one to two pumps running; (b)Flow changes with one to two pumps running.

regression through the following equations:

$$T_{out}(k+1) = a_{11}T_{out}(k) + a_{12}T_{in}(k) + c_1 \quad (8)$$

$$T_{in}(k+1) = a_{21}T_{out}(k) + a_{22}T_{in}(k) + c_2 \quad (9)$$

For the one-pump case:

$$F_{1p} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} = \begin{bmatrix} 0.596973 & 0.380452 \\ 0.243474 & 0.75596 \end{bmatrix} \quad (10)$$

and

$$G_{1p} = \begin{bmatrix} -0.493984 \\ 1.11595 \end{bmatrix} \quad (11)$$

Considering the two-pump case:

$$F_{2p} = \begin{bmatrix} 0.532277 & 0.433116 \\ 0.188163 & 0.809515 \end{bmatrix} \quad (12)$$

and

$$G_{2p} = \begin{bmatrix} -0.794684 \\ 1.12695 \end{bmatrix} \quad (13)$$

The process noise covariance is also estimated based on experimental data.

$$Q = \begin{bmatrix} \tilde{T}_{out}\tilde{T}_{out} & \tilde{T}_{in}\tilde{T}_{out} \\ \tilde{T}_{out}\tilde{T}_{in} & \tilde{T}_{in}\tilde{T}_{in} \end{bmatrix} \quad (14)$$

$$= \begin{bmatrix} 0.1 & 0.00064219 \\ 0.00064219 & 0.02 \end{bmatrix}, \quad (15)$$

where

$$\tilde{T}(k) = \mathbf{T}(k) - \hat{T}(k). \quad (16)$$

2.4 Parameter Uncertainty

The advantages of using a numerical model is that it finds a exact solutions, providing the model is correct. However, constructing an accurate numerical model for "real-world" domains is usually a difficult, error-prone and time-consuming process. Moreover, due to model inaccuracy, erroneous results may be generated, which may fail to cover all the ranges that need to be considered.

Here we emphasis parameter uncertainty or model error. We define a system error model as follows

$$\mathbf{F} = \overline{\mathbf{F}} + \Delta\mathbf{F} \quad (17)$$

where $\overline{\mathbf{F}}$ is the "real" (accurate) model of the system, $\Delta\mathbf{F}$ is the model error and $\mathbf{F}$ is the model incorporating the error. Using two different models ($\mathbf{F}$ and $\overline{\mathbf{F}}$), the two predictions based on the same estimates $\hat{\mathbf{x}}(k \mid k)$ are:

$$\hat{\mathbf{x}}(k+1 \mid k) = \mathbf{F}\hat{\mathbf{x}}(k \mid k) + \mathbf{G}\mathbf{u}(k) \quad (18)$$

and

$$\hat{\overline{\mathbf{x}}}(k+1 \mid k) = \overline{\mathbf{F}}\hat{\mathbf{x}}(k \mid k) + \mathbf{G}\mathbf{u}(k). \quad (19)$$

From equation (18) − equation (19) we have:

$$\hat{\mathbf{x}}(k+1 \mid k) - \hat{\overline{\mathbf{x}}}(k+1 \mid k) \quad (20)$$

$$= (\mathbf{F} - \overline{\mathbf{F}})\hat{\mathbf{x}}(k \mid k) \quad (21)$$

$$= \Delta\mathbf{F}\hat{\mathbf{x}}(k \mid k). \quad (22)$$

We term the model prediction error as

$$\delta\hat{\mathbf{x}}(k+1 \mid k) = \Delta\mathbf{F}\hat{\mathbf{x}}(k \mid k). \quad (23)$$

Thus

$$(\delta\hat{\mathbf{x}}(k+1 \mid k))^T(\delta\hat{\mathbf{x}}(k+1 \mid k))$$

$$= (\Delta\mathbf{F}\hat{\mathbf{x}}(k \mid k))^T(\Delta\mathbf{F}\hat{\mathbf{x}}(k \mid k))$$

$$= (\hat{\mathbf{x}}(k \mid k))^T(\Delta\mathbf{F})^T(\Delta\mathbf{F})(\hat{\mathbf{x}}(k \mid k)) \quad (24)$$

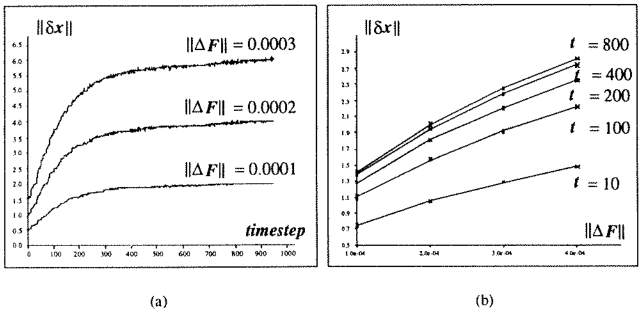


Figure 6: The relation between the model error and prediction error.

Or

$$\sum_j \delta x_{j\,j}^2 = \sum_j x_j^2 \sum_{ij} \Delta \mathbf{F}_{ij}{}^2 \qquad (25)$$

Here δx_j denotes the element of $\delta \hat{x}$, x_j is the element of $\hat{x}$ and $\Delta \mathbf{F}_{ij}$ is the element of $\Delta \mathbf{F}$.

Alternatively, we can rewrite equation (25) as the norm of the vectors:

$$||\delta x||^2 = ||\hat{x}||^2 ||\Delta \mathbf{F}||^2 \qquad (26)$$

Equation (26) shows the relationship between the model error and prediction error. Figure 6(a) shows a plot of $||\delta x||$s against timestep when given a number of fixed $||\Delta \mathbf{F}||$s. (Here $||\hat{x}||$s are the temperature estimates from an experiment using one boiler start-up process.) Figure 6(b) shows how $||\delta x||$ changes against $||\Delta \mathbf{F}||$ when we consider different time points. Using purely numerical modelling techniques, it can be seen that model errors can have substantial effects on system predictions.

3 Integration: Semi-quantitative Model Building

Several recent papers have focussed on the relationship between qualitative simulation and numerical simulation. One of the notable approaches is the idea of landmark refinement (Q2)[1]. This aims to employ quantitative information to refine qualitative landmarks; to make better predictions about model trajectories than are possible with pure qualitative simulation, and to prune a tree of qualitative behaviours as it is generated. Dvorak's MIMIC [5, 4] used Q2 for his dynamic system monitoring and diagnosis. However, Q2 suffers from suboptimal and often rather poor quantitative inference. Step size refinement (Q3 [2]) has been developed which is meant to improve Q2's quantitative results by producing progressively smaller step sizes. Another distinctive method is QP theory based approach which uses qualitative model to predict and explain the behaviours generated by a numerical model ([9] and SIMGEN [10]). Causal ordering was used on the qualitative models to guide explanations. The explanations also incorporated numerical information produced by the numerical simulation module. The limitation of this approach is that it requires a comprehensive domain model and a total envisionment. A number of other papers considered the abstraction of interval valued information into qualitative simulation. The general problem of measurement interpretation can be split into two cases, figuring out what is happening in a system at a particular time (taking one look) [6, 7, 8] and describing what is happening over a span of time DATMI [3].

3.1 Generation of the Semi-quantitative Model

From our analysis of numerical and qualitative modelling, we can see the following points: using system identification methods to obtain a numerical model is relatively easy given the sensing system, therefore, the numerical state space model formulation is used to describe the system. However models constructed in this way give little physical inside, as the parameters of the model have no direct physical meaning, they are used only as tool to provide a description of the system's overall behaviour. While on the other hand, the qualitative model derived from the fundamental balance equations provides better causal explanation and more intuitive insight into system behaviour. Thus, qualitative knowledge is incorporated as a guide to the numerical prediction process and also to provide an indication of the necessity or otherwise of using more complex data fusion techniques. Therefore, our approach is to develop a semi-quantitative or semi-qualitative model of the system which takes advantage of both numerical and qualitative method.

Using the state transition form described in Equation (6), the state transition model matrix and input model are described in the following form:

$$F = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \qquad (27)$$

and

$$G = \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_n \end{bmatrix} \qquad (28)$$

Each element of the state transition matrix, F, or input matrix, G, is a purely numerical value. The dimension n is decided by the number of the parameters. The corresponding semi-quantitative models follow the same formulation but each corresponding element of the matrices is an interval value $[a, b]$ $(a \ll b)$ which can be one of the following cases:

- $a = b$, which is $[a, a]$ when it is a fully specified value, the interval endpoints are identical.
- $a \neq b$, where both a and b are numerical values, thus $[a, b]$ is a real range value, where the true value falls into this range.
- $a \neq b$, where either a or b or both are qualitative values, eg. $(-\infty, b]$, $(0, \infty)$ or $(-\infty, \infty)$.

The semi-quantitative model of the system is initially generated by taking measurements during a number of runs of the system under different conditions, including different durations, and different situations, eg. different initial states (temperature values in our application). The original system design parameters can also be a source of information when making decision on the initial range of the parameters.

The principle of finding this initial interval matrix is independent of the application system. For a particular physical system with which we are concerned, we have a sensing network as described earlier. Thus we are able to take measurements from time to time. The measurements made can be used to relate the quantitative model to the qualitative model.

Having a number of experimental runs, we can obtain a group of corresponding numerical models F_1, F_2, ..., F_m (all $n \times n$ matrices) and G_1, G_2, ..., G_m. (all $n \times 1$ matrices.) using the method discussed in Section 2.3. The new semi-quantitative state space model $F_{interval}$ is then generated in the following way. Each element of the matrix is an interval value which takes the minimum and maximum values from the corresponding element of F_i and G_i, that is:

$$a_{ij} = min\{a_{ij_{F1}}, a_{ij_{F2}}, \cdots, a_{ij_{Fm}}\} \tag{29}$$

and

$$b_{ij} = max\{b_{ij_{F1}}, b_{ij_{F2}}, \cdots, b_{ij_{Fm}}\}. \tag{30}$$

Input matrix:

$$c_i = min\{c_{i_{F1}}, c_{i_{F2}}, \cdots, c_{i_{Fm}}\} \tag{31}$$

and

$$d_i = max\{d_{i_{F1}}, d_{i_{F2}}, \cdots, d_{i_{Fm}}\}. \tag{32}$$

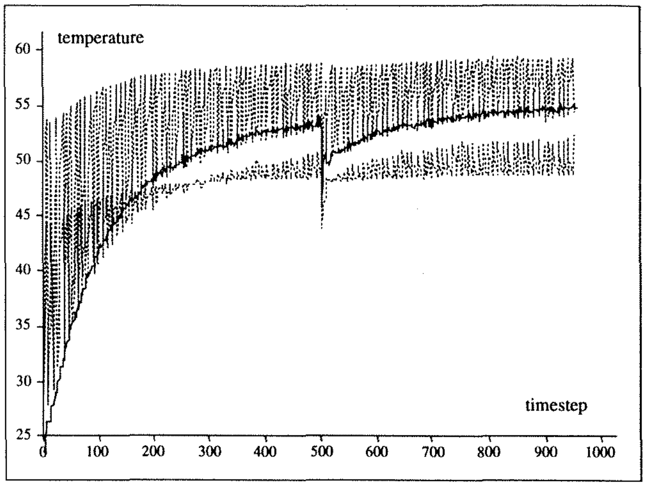


Figure 7: Dotted lines: boiler output temperature prediction ranges; solid line: real measurements. Interpolation time step $n = 10$.

We term the range valued matrix an *interval matrix* (following [13]). The semi-quantitative form of the system model and input model are denoted as:

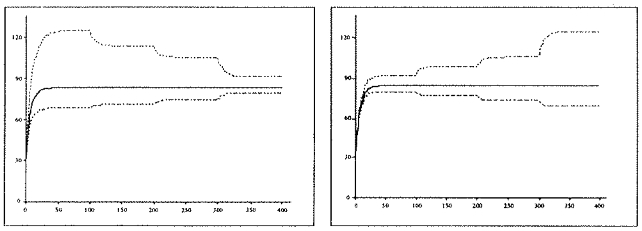
$$[F_{interval}] = \begin{bmatrix} [a_{11}, b_{11}] & [a_{12}, b_{12}] & \cdots & [a_{1n}, b_{1n}] \\ [a_{21}, b_{21}] & [a_{22}, b_{22}] & \cdots & [a_{2n}, b_{2n}] \\ \vdots & \vdots & \ddots & \vdots \\ [a_{n1}, b_{n1}] & [a_{n2}, b_{n2}] & \cdots & [a_{nn}, b_{nn}] \end{bmatrix}, \tag{33}$$

$$[G_{interval}] = \begin{bmatrix} [c_1, d1] \\ [c_2, d_2] \\ \vdots \\ [c_n, d_n] \end{bmatrix} \tag{34}$$

When two variables in the state vector are not related, the corresponding element in the matrix is zero. When there is at least one element in the original interval matrix which is a purely qualitative value, like $(0, \infty)$, $(-\infty, \infty)$, the qualitative simulation process is used to predict the system behaviours initially until a real valued interval is found to replace the qualitative interval.

3.2 The Prediction

Having found the semi-quantitative models of the system, $F_{interval}$ and $G_{interval}$, the predictions can be made based on the interval matrices. The interval analysis techniques developed by Moore [13, 14] form the basis for interval calculation. The individual



(a) (b)

Figure 8: (a)Semi-quantitative model predictions (dotted lines) approach the unique numerical model prediction (solid line) when reducing the range information of the model. (b)The predictions (dotted lines) made by the semi-quantitative model have excessive widths when the elements of the model have excessive range values, they still include the pure numerical prediction (solid line), but approach the qualitative prediction.

arithmetic operations $\{+, -, *, /\}$ are defined by:

$$\begin{aligned} [a,b]+[c,d] &= \{x+y : x\in[a,b], y\in[c,d]\} \\ &= [a+c, b+d] \end{aligned} \tag{35}$$

$$\begin{aligned} [a,b]-[c,d] &= \{x-y : x\in[a,b], y\in[c,d]\} \\ &= [a-d, b-c] \end{aligned} \tag{36}$$

$$\begin{aligned} [a,b][c,d] &= \{xy : x\in[a,b], y\in[c,d]\} \quad (37) \\ &= [min(ac,ad,bc,bd), max(ac,ad,bc,bd)], \end{aligned}$$

$$\begin{aligned} [a,b]/[c,d] &= \{x/y : x\in[a,b], y\in[c,d]\} \\ &= [a,b][1/d, 1/c], for 0 \notin [c,d] \end{aligned} \tag{38}$$

However, the propagation of interval matrices may result in the excessive widths for the range information. Therefore, for a given system, the prediction made based on this semi-quantitative model will be a subset of the prediction that the pure qualitative model has made and it will include the exact behaviour as predicted by an accurate model. When the range information in the interval matrices reduces (which in general is the case when the model error $\Delta F \in (0, inf)$ decreases) the prediction, will reduce its range and approach the unique real solution. This is demonstrated in Figure 8(a). Figure 8(b) shows the reverse case. Here when widening the constraints on the range information (ΔF increases), the semi-quantitative model predictions approach the purely qualitative one.

3.3 Measurement Interpolation

To avoid problems with divergent ranges, a measurement interpolation method was developed. An algorithm is designed to keep the predictions convergent within certain ranges involving the use of measurements to "refine" state estimation or interpolating new measurements to replace the estimate.

As F and G are interval matrices, after one prediction cycle, the prediction vector is an interval vector, shown in the following equation:

$$[\hat{\mathbf{x}}(k+1 \mid k)] = [\mathbf{F}]\hat{\mathbf{x}}(k \mid k) + [\mathbf{G}]\mathbf{u}(k) \tag{39}$$

Further cycles may further widen the intervals. (With the square brackets denoting the interval matrices or vectors). To avoid an unbounded increase of the interval width, we take the intersection of the measurements with the state estimate at every n time steps:

When $k = l \cdot n;$ (40)
where n = predefined number of time steps,
and $l = 0, 1, \cdots, l \cdot n \leq$ current time step.

$$\hat{\mathbf{x}}(k \mid k)_{new} \mid_n = \hat{\mathbf{x}}(k \mid k) \cap \mathbf{z}(k) \mid_n \tag{41}$$

The importance of using the measurements to refine the estimate is that the observation values are always within reasonable small ranges. (That is: $[obs - \Delta, obs + \Delta]$, where Δ is the measurement precision.) Thus by taking the intersection of both, the interval width of the next step's prediction can be bound within small ranges.

The inherent principle idea works for the following cases. Assume:

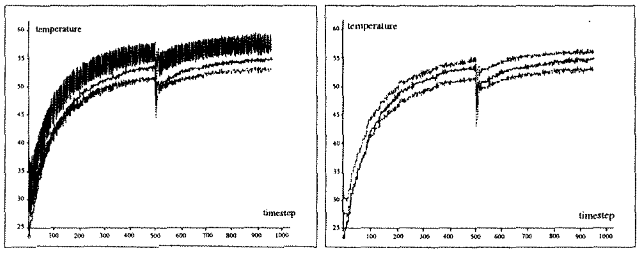
$$\hat{\mathbf{x}}(k \mid k) \in [l_i, l_j] \quad and \quad \mathbf{z}(k) \in [l_p, l_q]. \tag{42}$$

when

$$\begin{aligned} either \quad & l_p < l_j, and \quad l_q > l_i; \\ or \quad & l_i < l_p < l_j \end{aligned}$$

Then the left hand side of equation (41) is non-zero. However when $l_q < l_i$, or $l_p > l_j$, equation (41) is zero, the above algorithm does not work in a straightforward way. This is the case that the state estimated is inconsistent with the measurement. This represents one of the following cases:

- The system model needs to be modified so that when the system behaves normally, the estimate should be consistent with the real measurements;



(a) (b)

Figure 9: (a) Interpolation time step $n = 3$, (b) Interpolation time step $n = 2$.

- The conflict shows that the system is in an abnormal state; further analysis techniques will be used;
- The abnormal state model is to be augmented based on both the new measurements and qualitative knowledge about the physical systems.

Here we explain the algorithm used through some examples. We consider the same case discussed in Section 2 that transits the state from one pump to two pumps. Figure 7 shows the predictions made by the semi-quantitative model with every 10 time steps ($n = 10$) of the measurement interpolations. Figure 9(a) shows results with $n = 3$. And finally Figure 9(b) shows the refinement time step with $n = 2$.

4 System Monitoring and Fault Detection

The interval estimates and predictions are used to perform system monitoring and fault detection. As interval data provides us with a different type of information from conventional single valued data, different algorithms are also designed here to deal with interval values.

4.1 Monitoring: Qualitative Interpretations

To monitor the physics of the system and to understand it using common sense knowledge, we abstract range information to sign information. This is one way of interpreting the qualitative information from semi-quantitative information. The interpretation criteria are described below.

Suppose interval values change from A to B, $A \in [l_m, l_n]$, $B \in [l_\alpha, l_\beta]$. They can be interpreted into

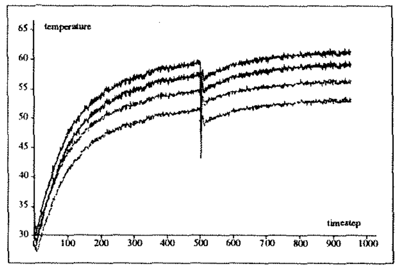


Figure 10: Example of two range valued temperatures; Solid lines: $[T2_{lo}, T2_{hi}]$, dotted lines: $[T1_{lo}, T1_{hi}]$.

t.step	qual.int	t.step	qual.int	t.step	qual.int
4	std-dec	9	std-inc	14	std-inc
19	std-inc	24	std-inc	29	std-inc
34	std-inc	39	std-inc	44	std-inc
49	std-inc	54	std-inc	59	std-inc
64	std-inc	...	...	489	std-dec
494	std-inc	499	std-dec	504	dec
509	inc	514	std-dec	519	std-inc
524	std-dec	529	std-inc	534	std-mag
539	std-dec	544	std-inc	549	std-inc
554	std-inc	...	...	919	std-dec
924	std-inc	929	std-inc	.934	std-dec
939	std-inc	944	std-inc	949	std-inc

Figure 11: Qualitative Interpretation

three different types of qualitative changes defined as follows:

$$\begin{array}{lll} inc & \text{(increase;)} & if l_\alpha \geq l_n \\ dec & \text{(decrease;)} & if l_\beta \geq l_n \\ std & \text{(steady;)} & otherwise. \end{array} \quad (43)$$

The level of detail that the interpretation involves depends on how close the two interval values A and B are chosen. Figure 10 gives two range valued temperature sequences. Figure 11 shows the qualitative interpretation based on $B(timestep) - A(timestep) = 5$. However, the level of detail may be changed over the interpretation of one sequence. Either at some crucial points (eg. state transition) or when there are some significant changes of the qualitative states (eg. from *inc* to *dec*), higher level of details can be introduced.

By continuing this qualitative interpretation of the range information over time, a qualitative understanding of the physical system can be obtained incrementally. Domain-specific knowledge about the state and the transition possibilities can be used to suggest the interpretation which is most likely. When no consistent interpretation exists, faulty hypotheses may be generated.

4.2 Fault Detection

The interval estimates and predictions are used to perform system monitoring and fault detection. As interval data provides us with a different type of information from conventional single valued data, different algorithms are also designed here to deal with interval values. Before giving detailed explanation of the algorithms, an assumption is introduced first. That is the systems considered do not have any unknown controlled state changes/transitions. Any state changes are regarded as faults. As a consequence, there will be "abrupt changes" in the sensor readings. At this stage, only temperature readings are considered. Pressure and flow readings will be taken into account in the diagnosis process.

Two methods are designed to analyse the interval sequences and detect abrupt changes.

4.2.1 Smoothing method

Assume that we have a sequence of prediction vectors; they represent interval information, denoted as:

$$([\hat{\mathbf{z}}(k)] \mid k = 0, 1, \cdots, n)$$
$$\text{where} \quad \hat{\mathbf{z}}(k) \in [\hat{\mathbf{z}}_{lo}(i), \hat{\mathbf{z}}_{hi}(i)], \qquad \text{and } i \in (0, n).$$

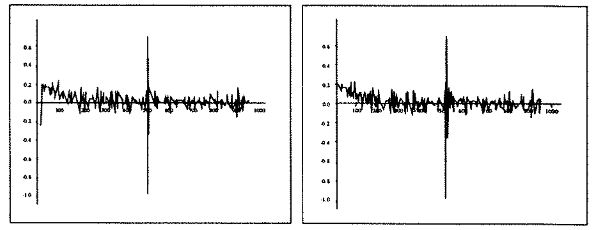
By choosing a time width, which we term as the window size τ, we can analyse the changes of higher bound and lower bound of this prediction sequence in the following way:

$$\frac{\hat{\mathbf{z}}_{hi}(t+\tau) - \hat{\mathbf{z}}_{hi}(t)}{\tau} = \Delta\mathbf{Z}_{hi} \tag{44}$$

$$\frac{\hat{\mathbf{z}}_{lo}(t+\tau) - \hat{\mathbf{z}}_{lo}(t)}{\tau} = \Delta\mathbf{Z}_{lo} \tag{45}$$

As an example, given the two sequence of temperature predictions in Figure 10, by running of the "smoothing" program to $[T1_{lo}, T1_{hi}]$, the corresponding $\Delta\mathbf{Z}_{hi}$ and $\Delta\mathbf{Z}_{lo}$ obtained are shown in Figure 12. From Figure 12 we can see that: this process has smoothed small changes, but retains the large changes. Therefore, by checking $max(\Delta\mathbf{Z}_{hi})$ and $max(\Delta\mathbf{Z}_{lo})$, the abrupt change points or failure points can be detected. This change detection process is done from timestep zero to the current time step. When $\tau \longrightarrow 0$, then the above equations become:

$$\frac{d\hat{\mathbf{Z}}_{hi}}{dt} = \Delta\mathbf{Z}'_{hi} \quad \text{and} \quad \frac{d\hat{\mathbf{Z}}_{lo}}{dt} = \Delta\mathbf{Z}'_{lo}, \tag{46}$$



(a) ΔZ_{hi} ($\tau=5$) (b) ΔZ_{lo} ($\tau=5$)

Figure 12: Higher bound and lower bound of the range value analysis.

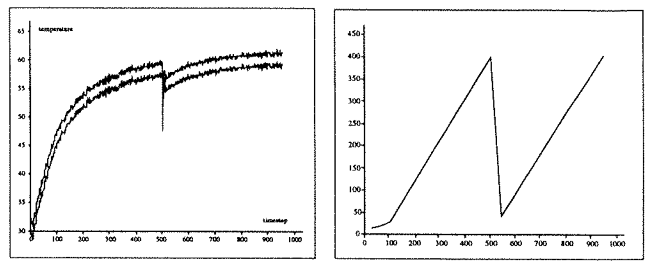


Figure 13: Interval changes detection example 1

which show the changing rate of the range information. The window size τ here can be adjusted according to specific application needs.

4.2.2 Non-smoothing method

Another way of looking at changes of interval information quantitatively is the non-smoothing method. Rather than considering the higher bound or lower bound of the interval values separately, here each interval value as a whole will be compared with the previous time step value. The algorithm continuously carries out the following process, from the current time step scanning backwards to the first time step:

$$\begin{array}{rl} \text{If} & \hat{\mathbf{Z}}_{lo}(k) \geq \hat{\mathbf{Z}}_{hi}(k-1) \\ \text{Then} & k-1 \rightarrow k, \text{ and } k-2 \rightarrow k-1 \\ \text{Else} & k \rightarrow k \text{ and } k-2 \rightarrow k-1 \end{array} \tag{47}$$

Figure 13 shows an example of the execution of this algorithm on the sequences in Figure 10. The algorithm will pick up any abrupt changes along the time sequence. Figure 14 is another demonstration of the algorithm.

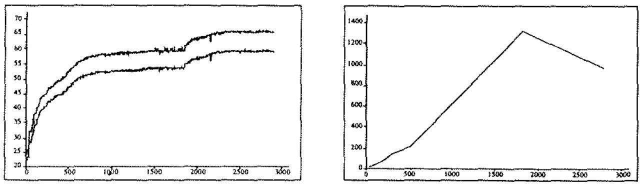


Figure 14: Interval changes detection example 2

5 Conclusions and Future Work

This paper describes the work done towards integrating qualitative reasoning into numerical data fusion. Presented here is a methodology for generating the combined model, and analysing the interval information for the purpose of system monitoring and fault detection. Various algorithms developed have been implemented on a real system, process plant. Effort has been made in integrating the results from the engineering community and from the qualitative community. Further work along this line will be carried out, emphasizing in particular the use of qualitative reasoning techniques to explain various phenomena.

Future work also includes using the integrated technique to perform the diagnosis task. Although a semi-quantitative model can be generated, it describes only standard behaviour. Therefore, it is impossible to use it to simulate unforeseen situations. However, considering the process plant system we have been studying, we may have a fixed number of qualitative model based physically on the principle of violation of continuity or energy equations. Then we should be able to deduce, for example, from the successful violation of the energy constraint or mass flow constraint, that there exists a particular type of fault in a particular location.

Acknowledgements

Here we gratefully acknowledge Prof. B. Kuipers and his students D. Clancy and B. Kay for their providing the QSIM software and support for its use. This work is supported in part by SERC/IED/1199.

References

[1] D. Berleant and B. Kuipers. Qualitative and quantitative simulation: Bridging the gap. Technical Report AI90-158, U. of Texas Dept. Comp. Sci., 1990.

[2] D. Berleant and B. Kuipers. Qualitative-numerical simulation with q3. In B. Faltings and P. Struss, editors, *Recent Advances in Qualitative Physics*. The MIT Press, 1992.

[3] D. DeCoste. Dynamic across-time measurement interpretation. *Artificial Intelligence Journal*, 51(1-3):273–342, 1991.

[4] D. Dvorak. *Monitoring and Diagnosis of Continuous Dynamic Systems Using Qualitative Simulation*. PhD thesis, University of Texas AI Lab., 1992.

[5] D. Dvorak and B. Kuipers. Model-based monitoring of dynamic systems. In *Int. Joint Conf. Artificial Intelligence*, pages 1238–1243, 1989.

[6] K. Forbus. Measurement interpretation in qualitative process theory. In *Int. Joint Conf. Artificial Intelligence*, volume 1, pages 315–320, 1983.

[7] K. Forbus. Interpreting measurements of physical systems. In *National Conference on Artificial Intelligence*, pages 113–117, 1986.

[8] K. Forbus. Interpreting observation of physical systems. *IEEE Trans. Systems Man and Cybernetics*, SMC-17(3):350–359, 1987.

[9] K. Forbus and B. Falkenhainer. Self-explanatory simulations: Integrating qualitative and quantitative knowledge. In B. Faltings and P. Struss, editors, *Recent Advances in Qualitative Physics*, pages 49–66. MIT Press, 1992.

[10] K. D. Forbus. The qualitative process engine. In D.S. Weld and J. de Kleer, editors, *Readings in Qualitative Reasoning about Physical Systems*. Morgan Kaufmann Publishers, INC, 1990.

[11] Y. Gao and H. Durrant-Whyte. A transputer-based sensing network for process plant monitoring. In *Third Int. Conf. Transputers and Applications*. IOS Press, 1991.

[12] K.A.Loparo, M.R.Buchner, and K.S.Vasudeva. Leak detection in an experimental heat exchanger process: A multiple model approach. *IEEE Trans. Automatic Control*, 36(2):167–177, February 1991.

[13] R. E. Moore. *Interval Analysis*. Preentice-Hall, Inc., 1966.

[14] R. E. Moore. *Methods and Applications of Interval Analysis: SIAM Studies in Applied Mathematics*. SIAM, 1979.