Chapter 3
QUALITATIVE SIMULATION OF HUMAN REASONING ABOUT PROCESSES

3.1 INTRODUCTION

The most common technique that science uses to describe physical laws is mathematics. Since classical mathematics is better suited for describing constraints than mechanisms, it has resulted to have a focus on constraints on behaviours rather than on the mechanisms by which behaviours are achieved. This research attempts to describe some qualitative and informal techniques that humans use naturally to reason about these mechanisms. Basically, a theory similar to that of human reasoning is developed. Formal quantitative theories explain the behaviour of electrical and mechanical systems. However, these theories bear little resemblance to the informal qualitative reasoning of human beings. For example, network theory is a very powerful tool for analysis, but an engineer uses it only as a last resort. Most of the time he uses informal and qualitative techniques. The generality and simplicity of the qualitative theories originate from their use of mathematics. The experience of artificial intelligence research has been that systems which embody a great deal of the classical knowledge fail at tasks successfully accomplished by human beings with the same knowledge. The major reason for failure is the lack of more qualitative common sense knowledge.

Humans prefer to understand systems in terms of causes and effects, rather than simultananeous constraints. Human experts have
shallow as well as deep knowledge of their domain. Mathematical models only have shallow knowledge about a system, and for complex systems these become quite involved. Mathematical models cannot predict the behaviour of a system since they do not have deep knowledge about the components of a system.

3.2 QUALITATIVE SIMULATION

The last decade has seen significant progress towards the development of formal methods for qualitative reasoning. Qualitative simulation (QS) provides explanation from deep knowledge as compared to shallow knowledge characteristics of many symbolic models. Qualitative modeling is thus becoming the heart of model based reasoning for automated diagnosis, control and industrial training systems.

QS consists of a number of different operations. A set of constraint equations describing the relevant structural relationships in a system may be derived by examination of its physical structure. The possible behaviours may be predicted by QS from constraint equations and an initial state. QS thus predicts behaviour of a system from the qualitative constraint equations.

A differential equation describes a physical system in terms of a set of state variables and constraints. The solution is a function representing the behaviour of the system over time. A description of structure in terms of constraint equations is an abstraction of the same system. QS is intended to yield a corresponding abstraction of its behaviour.
There are four reasons for the development of qualitative models of physical systems.

The motivation for the initial work in QR came from the development of an intelligent tutoring system for troubleshooting electronic circuits called Sophie III. In this the requirement was simple models of electronic circuits so that a student can understand the function of the device. This tutoring system also provides conventional reliable mathematical model. However, a qualitative description should support a simpler computational mechanism than the
detailed model. Moreover a conceptual understanding of the operation is important.

Traditional methods may be ineffective due to lack of knowledge of the system description or because the development costs are non-viable. This is often the case in the chemical or process industries where chemical reactors, flow processes and thermal systems are difficult to characterise.

QS provides modeling paradigms that accord more closely with our common sense intuition of the operation of physical systems. Such descriptions do not require that the modeller, or the person using the model, have a knowledge of physics to understand the way a system behaves. In fact, people interact with the physical world based on their experience and intuition and not on an understanding of the principles of physical laws.

QS provides modeling methods based on the principles of knowledge based systems. This means representing the model in a declarative format so that the same description can be used for a number of different purposes and for reasoning with partial, uncertain or incomplete information. Additionally, QS provides effective explanation facilities. This aspect is, of course, vitally important for real-time applications, where the need to be able to justify a given decision is crucial to its acceptance and verification.
3.3 CONFLUENCE THEORY

A brief description of the qualitative calculus of Dekleer and Brown [33-37] is given. The most basic feature of a QS model is that it has qualitative rather than continuous variables. The finite value set contains three numbers: \{+, -, 0\}. The values of variables may thus be positive, negative and zero. Derivatives may be increasing, decreasing and constant. The qualitative calculus is based upon sign algebra. Table 3.1 gives addition and subtraction rules in qualitative arithmetic. First row and first column give the value of the variables being added or subtracted. The value of the result is given by the other entries in the table. A 'X' indicates that the value is indeterminate. A qualitative equation is called a confluence. The confluences are similar to ordinary equations, but have an additional truth condition. An ordinary equation may be true or false, while a confluence can be indeterminate. Indeterminate solutions are just as acceptable as those that are true.

Only three constituent types are used to model certain devices: components, conduits and materials. Materials are transformed by components and transported by conduits. Components are defined as functional relationship between input and output. Every component is associated with a finite number of qualitative states, where each state is described by a set of confluences.
Table 3.1
Qualitative Arithmetic
Addition

<table>
<thead>
<tr>
<th>Variable</th>
<th>+</th>
<th>-</th>
<th>0</th>
<th>X</th>
</tr>
</thead>
<tbody>
<tr>
<td>+</td>
<td>+</td>
<td>X</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>-</td>
<td>X</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>0</td>
<td>+</td>
<td>-</td>
<td>0</td>
<td>X</td>
</tr>
<tr>
<td>X</td>
<td>+</td>
<td>-</td>
<td>0</td>
<td>X</td>
</tr>
</tbody>
</table>

Subtraction

<table>
<thead>
<tr>
<th>Variable</th>
<th>+</th>
<th>-</th>
<th>0</th>
<th>X</th>
</tr>
</thead>
<tbody>
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<td>+</td>
<td>+</td>
<td>+</td>
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<tr>
<td>-</td>
<td>-</td>
<td>X</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>0</td>
<td>-</td>
<td>+</td>
<td>0</td>
<td>X</td>
</tr>
<tr>
<td>X</td>
<td>-</td>
<td>+</td>
<td>X</td>
<td>X</td>
</tr>
</tbody>
</table>

Example 3.3.1

Consider a U-tube, which consists of two partially filled tanks and connected at the bottom by a thin tube as shown in Fig. 3.2. U-tube is in equilibrium when it receives an increment of water to one side. A new equilibrium will now be established with the level in both tanks higher than before.
FIG. 3.2: THE U-TUBE IS IN EQUILIBRIUM WHEN AN INCREMENT OF WATER IS ADDED

FIG. 3.3: MODEL USING DEKLEER AND BROWN'S METHOD

PART A
\[ P_A \]
\[ F_{r,A} \]
\[ F_{A-B} \]
\[ \delta P_A + [F_{A-r}] + [F_{A-B}] = 0 \]

PART C
\[ [F_{A-B}] + [F_{B-A}] = 0 \]
\[ [F_{A-B}] = [P_A - P_B] \]

PART B
\[ P_B \]
\[ F_{B-A} \]
\[ \delta P_B + [F_{A-B}] = 0 \]

FIG. 3.3: MODEL USING DEKLEER AND BROWN'S METHOD
Part A and Part B of the tube are two components connected by a thin tube C. Pressure and rate of flow are not directly represented but each component would have appropriate quantities for these two parameters.

Model of the situation is shown in Fig. 3.3. Each component and connection is associated with confluences.

Table 3.2
Temporal Sequence of Selected Values

<table>
<thead>
<tr>
<th>Quantities</th>
<th>t₁</th>
<th>t₂</th>
<th>t₃</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fr-A</td>
<td>+</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Fₐ₋₋ₖ</td>
<td>0</td>
<td>+</td>
<td>0</td>
</tr>
<tr>
<td>Pₐ</td>
<td>= Pₖ</td>
<td>&gt; Pₖ</td>
<td>= Pₖ</td>
</tr>
<tr>
<td>δPₐ</td>
<td>+</td>
<td>-</td>
<td>0</td>
</tr>
</tbody>
</table>

Pₐ and Pₖ are the pressures in part A and part B of the U-tube. Pressure in part A varies with the flow of water from source may be a room to part A (Fr-A) and from part A to part B (Fₐ₋₋ₖ). Initially water flows from room to part A so that Fr-A is +ve and Fₐ₋₋ₖ is -ve. Pressure in part A(Pₐ) is equal to that in part B (Pₖ). The situation is depicted in Table 3.2 in time slot t₁.

At t₂, Pₐ becomes greater than Pₖ and water flows from A to B so that Fₐ₋₋ₖ is +ve. As water flows from A to B, pressure in part A naturally decreases and δPₐ is -ve. In equilibrium state at t₃, Pₐ again becomes
equal to $P_B$. Thus, the level of water in parts A and B becomes equal. Obviously, there is no flow of water and $\delta P_A$ is zero.

3.4 QSIM ALGORITHM

The three valued quantity space of Dekleer and Brown \{+, 0, -\} is impractical [38]. A contemporary quantity space, consisting of open intervals and real valued landmarks was developed as part of the QSIM algorithm [38-40]. This has received the greatest attention and has come nearest to the practical application. The landmark values are associated with physical parameters e.g. top of the tank and define the operating range for the variables. In QSIM, the quantity space consists of a qualitative magnitude taken from the landmark quantity space and a qualitative derivative taken from the three valued space interpreted as increasing, steady or decreasing. This permits a reasonable representation of the value of a variable. QSIM is a powerful simulation algorithm and is based on the following observations:

- The domain of a variable representing a physical parameter can be partitioned into a small number of landmark points and intervals between them.

- Knowledge of the direction of change of a variable in conjunction with its qualitative magnitude is enough to determine the qualitative properties of its evolution.

- To determine the qualitative behaviour of a system, it is sufficient to know a functional relationship between two variables and corresponding pairs of landmark values.
A significant difference between QSIM and other algorithms [41-43] is its ability to create new landmarks through simulation. A variable is not only qualitatively described by its qualitative magnitude (QMAG) but also by its direction of change, QDIR, which can be either increasing, steady or decreasing. The pair (QMAG, QDIR) is called the qualitative value (QVAL) of a variable. The set of QVALS of all the system variables is the qualitative state of the system.

The set of all possible states of a system is restricted by relations between variables, called constraints. Constraints may model arithmetic relationships like add (x,y,z), mult (x,y,z) or minus (x,y,z), differential relationships like deriv (x,y) or functional relationships like M+ (x,y). The last functional relationship states that some monotonically increasing function M+ exists between x and y. For example, one can express the relation between the amount of a liquid in a tank and its level by M+ (LEVEL, AMOUNT).

The set of all the variables with their associated quantity spaces and the set of all the constraints form qualitative differential equations. Sometimes the current QDE may not be appropriate to describe the structure. For example, the M+ relation is not valid if the tank overflows. The range of variables for which a QDE is valid is called an operating region.

Given a qualitative description of a system in terms of variables and constraints, QSIM starts from an initial state and determines the possible future states. If several possibilities are compatible with the constraints, QSIM branches to every possibility, QSIM reapplyes this process to every
newly created state and the result is a tree of possible behaviours. In other words, QSIM algorithm produces spurious predictions. It means some behaviours derived from a qualitative model do not correspond to any possible behaviour of the system consistent with the model.

Example 3.4.1

Consider, for example, a ball thrown in the air. It leaves the ground at time $t_0$ with an initial vertical speed $V_0$. In case of no friction, its acceleration is equal to constant gravity $g$. The model and the predicted behaviour of the system are as shown in Figs. 3.4 and 3.5.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Landmarks</th>
<th>Constraints</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Y$</td>
<td>0</td>
<td>$+\infty$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$d/dt \ (Y,V)$</td>
</tr>
<tr>
<td>$V$</td>
<td>$-\infty$</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$+\infty$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$d/dt \ (V,A)$</td>
</tr>
<tr>
<td>$A$</td>
<td>$-\infty$</td>
<td>$g$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Constant $\ (A)$</td>
</tr>
</tbody>
</table>

FIG. 3.4 : FRICTIONLESS MOTION OF BALL.

FIG. 3.5 : EXPECTED BEHAVIOUR OF THE BALL.
The qualitative behaviour of frictionless motion of ball is clear: it first goes up, reaches a maximum height at time $t_1$ and comes down to touch the ground at time $t_2$. This behaviour is predicted by QSIM.

3.5 LIMITATIONS OF QS

The primitives of QS models are simple, few and intuitively appealing. However, a number of technical problems arise when QS is applied to full scale industrial applications. The limitations of QS method fall mainly into following two categories:

- Qualitative ambiguity
- Lack of temporal information

The first occurs because of inherent ambiguity of qualitative calculus. The spurious behaviours tend to obscure the real behaviour. One way to eliminate these spurious behaviours is to introduce new variables [44] representing potential and kinetic energy and to maintain that the total energy is constant. Reasoning about energy has an important place in common sense understanding of the physical world. One can draw many conclusions about a system based on qualitative analysis of energy balance. But this approach has several drawbacks e.g.

- Additional variables must be added to the system model, reducing its simplicity. QSIM needs to be given expressions for $C$ and $N$ in terms of these variables. $C$ and $N$ are conservative and non-conservative work respectively. Signs of the variables should also be known.
The simulator must be given additional information that is implicitly contained in existing constraints. It should be able to determine whether the system is conservative by analysing the constraint structure.

The second limitation occurs as present techniques have no explicit information on temporal durations [47,48]. In order to overcome this limitation two approaches are being developed. Firstly, explicit temporal duration can be associated with each qualitative state [48]. Temporal constraints are then used to propagate the qualitative values and their durations. The propagation of durations result in temporal reasoning which is independent of qualitative values. Secondly, the representation of the qualitative state can be extended to allow ordering information on the relative rates of change of variables [49,50]. This method enables to determine temporal duration also known as persistence time.

Besides these limitations, it is difficult to incorporate causal explanation to account for the propagation of disturbances. Equations that describe the behaviour of dynamic systems make implicit reference to free variables. As soon as an equation set is completely specified, its solution set can be discovered. In the universe of pure mathematics, all constraints are satisfied simultaneously and immediately. Clearly, an equation does not encode required manipulations of mental models. An equation can constrain human inference, but cannot explain the process.
Iwasaki and Simon [51,52] suggested that simultaneous constraint satisfaction techniques are beyond unaided human capabilities. Unaided or natural inference about device behaviour, especially if the underlying equations have not been identified, is guided by causal ordering. Iwasaki and Simon observed that an equation is symmetric (simultaneous) where as causal ordering of constraints is directional (sequential). Dekleer and Brown [34] observed, "causality as a theory of how devices function provide many advantages. Because it is a theory of how the device achieves its behaviour rather than just what its behaviour is;.... it is now possible to ask what functional changes result from hypothetical structural changes". Causal explanation of transitions between equilibrium states is exactly the type of knowledge required for knowledge based cognition.

Causal ordering as proposed by Iwasaki and Simon [52] uses directed primitives but without a sign of effect. The exogenous variables of the system are used as the independent variables. The term exogenous describes activities in the environment that affect the system. Causal ordering produces a graph of dependencies by manipulating the quantitative equations describing the system. The possibility of incorrect causal arguments is avoided by detecting when the system of equations is undetermined. Success of causal ordering depends on two factors:

- A set of quantitative equations should be known.
- Exogenous variables should be known.
3.7 PROPOSED CAUSAL ORDERING IN NON LINEAR SYSTEMS

Basing the notion of causal dependence on exogenous parameters limits causal ordering to creating models of specific systems in specific modes of behaviour. The limitation to specific systems comes from the fact that exogenous variables often change when a system becomes part of a larger system. Also, the equations describing a system or object may vary drastically. In order to do diagnosis of device faults using knowledge of the causal relations in the domain, the system needs model consisting of structural knowledge in terms of device topology and relations among physical parameters, based on physical laws and expected behaviour of subcomponents. To determine causal ordering, the model need not specify the effects of the variables, but it should specify which variables affect other variables.

Iwasaki [51] has determined causal ordering of variables in linear systems, whereas most of the physical systems are non linear. Causal ordering can produce correct causal structure provided each equation represents a conceptually distinct mechanism. It is difficult to analyze a system of non-linear differential equations. Although in this work, non linear systems have been taken to show the causal dependency among the variables, there is no general technique for the analysis of all non linear systems. Particular classes of non linear systems have to be considered separately. The solution of non linear system is further complicated by the fact that the characteristics of non linear elements are specified graphically. Further, there is no simple mathematical description of these characteristics.
Example 3.7.1

Consider, a proportional integral or PI-controller as shown in Fig. 3.6. The principle of the controller is quite simple. The level sensor senses the level $L$ of liquid in the tank. The sensed value $L$ is compared with a set value $L_s$ by the controller. The difference between the two values is defined as the error $e$. The valve opening $v$ is a function of the error and the integral $i$ of error $e$.

![Diagram of a level-controlled tank](image)

The system variables are:

- $q_1$: volumetric inflow rate
- $A$: cross sectional area of the tank
- $L$: level of liquid in the tank
- $e$: error between level set $L_s$ and actual level $L$
- $v$: position of valve
- $q_2$: volumetric outflow rate
- $L_s$: set point

**FIG. 3.6: A LEVEL-CONTROLLED TANK**
\[ \frac{dL}{dt} = q_1 - q_2 \]  
\[ \text{...(3.7-1)} \]

Rate of change of liquid level in the tank is proportional to the difference of inflow and outflow rates. The position of valve \( v \) is given as:

\[ v = f_0 (i) + g_0 (e) \]  
\[ \text{...(3.7-2)} \]

Where \( f_0 \) and \( g_0 \) are functions of integral of error and error respectively. Integral function introduces non linearity in the system. The characteristic equation for valve position is given by equation (3.7-3) and is derived below:

\[ q_2 = v_{cv} \sqrt{P - P_a} \]
\[ P = P_a + \rho g L \]
\[ q_2 = v_{cv} \sqrt{P_a + \rho g L - P_a} \]
\[ = v_{cv} \sqrt{\rho \ g L} \]  
\[ \text{...(3.7-3)} \]

\[ q = q_1 - q_2 = A \frac{dL}{dt} \]  
\[ \text{...(3.7-4)} \]

\[ e = L_s - L \]  
\[ \text{...(3.7-5)} \]
The matrix of structural equations is as shown in Fig. 3.7.

\[
\begin{array}{cccccccc}
 & L_s & L & e & v & q_2 & q_1 & q & L' \\
1. & & & & & 1 & 1 & 1 & \\
2. & & & & 1 & & & 1 & \\
3. & & 1 & & 1 & & & 1 & \\
4. & & & 1 & & 1 & & 1 & \\
5. & 1 & & & 1 & & & 1 & \\
\end{array}
\]

**FIG. 3.7: THE MATRIX OF STRUCTURAL EQUATIONS.**

Each column in the matrix represents variables in the structural equations. Each row shows the variables, the structural equations use. First row gives the variables of equation (3.7-1) and so on.

The causal dependency among variables can be determined from the matrix of structural equations and is shown in Fig. 3.8.

**FIG. 3.8: THE CAUSAL STRUCTURE OF LEVEL CONTROLLER.**

The causal structure shows functional dependency among variables. I above the arrow between q and L indicates that the system is non-linear and L is integral of q. Equations that describe the mechanisms and determine the values of its individual variables are called structural
equations. To determine causal ordering, the model need not specify the effects of the variables, but it should specify which variables affect other variables directly. So, this method can be used with a qualitative model of a system. QM will depict the behaviour qualitatively and causal explanation about how behaviour is achieved is given by causal ordering.

**Example 3.7.2**

For an electrical engineer, a causal argument consists of a sequence of assertions about electrical quantities each of which hold as a consequence of previous assertions. Causal analysis produces a causal argument which is a qualitative description of how the circuit equilibrates -how it responds to perturbations from its equilibrium state. This description simulates the circuit’s equilibrium. The causal analysis process itself is a simulation. An electrical engineer will explain the operation of an electrical system in terms of a sequence of events each of which is caused by previous events. Each event is an assertion about some behavioural parameter of some constituent of the system. By discarding most of the details of the system, a sequential description of the behaviour of system can be extracted. This abstract characterization of circuit behaviour is sufficient for many purposes.

A change in one part of an electrical circuit can have immediate impact on every other part of the system. In order to conceive these changes they have to be ordered. As an example, a magnetic amplifier has been causally analysed here. It is assumed for simplicity that the amplifier considered is symmetric as shown in Fig. 3.9.
By the application of Kirchhoff’s voltage law and Ampere’s current law for the electric and magnetic circuits, the basic equations for the amplifier circuit can be written as:

\[ R_1 i_1 + N (\dot{\phi}_1 + \dot{\phi}_2) = V \]  
(3.7-6)

\[ R_1 i_2 + N (\dot{\phi}_1 - \dot{\phi}_2) = V_m \sin (\omega t + \theta) \]  
(3.7-7)

\[ N (i_1 + i_2) = L H_1 \]  
(3.7-8)

\[ N (i_1 - i_2) = L H_2 \]  
(3.7-9)

\[ H_1 = \frac{\phi_1}{\mu_0 A} + K\phi_1^3 \]  
(3.7-10)

\[ H_2 = \frac{\phi_2}{\mu_0 A} + K\phi_2^3 \]  
(3.7-11)

Where \( H_1 \) and \( H_2 \) are magnetic intensities of the cores 1 and 2. \( \phi_1 \) and \( \phi_2 \) are magnetic fluxes in the corresponding cores. Both windings have an equal number of turns \( N \) and equal ohmic resistances \( R_1 \), \( L \) is the
mean length of the magnetic path of the two cores, and $A$ is the
cross-sectional area.

$\mu_0$ = initial permeability of the core material

$K$ = an empirical constant

An approximate solution of the system equations yields

$$\phi_m = \frac{V_m}{2N} \left[ \omega^2 + \left( \frac{R_1}{2L_0} + 3K_1\phi_0^2 \right)^2 \right] \frac{L}{2}$$  \hspace{1cm} (3.7-12)

Where $L_0 = \frac{\mu_0 N^2 A}{L}$

and $K_1 = \frac{R_1 L K}{2N^2}$

Where $L_0$ is the initial inductance of one of the core windings. Also

$$\phi_0 = \frac{L_0 V}{NR_1}$$  \hspace{1cm} (3.7-13)

The approximation gives second and third harmonic components of

$$\phi_1 = \phi_0 + \phi_m \sin \omega t + A_2 \cos 2\omega t + B_3 \sin 3\omega t$$ \hspace{1cm} (3.7-14)

$$\phi_2 = \phi_0 - \phi_m \sin \omega t + A_2 \cos 2\omega t - B_3 \sin 3\omega t$$ \hspace{1cm} (3.7-15)

Where $A_2 = \frac{K_1 L_0 \phi_0 \phi_m}{R_1}$

and $B_3 = \frac{K_1 L_0 \phi_m^3}{2R_1}$

Approximate solution of the above equations give
\[
\begin{align*}
    i_1 &= \frac{V}{R_1} - \frac{N (\phi_1 + \phi_2)}{R_1} \\
    i_2 &= \frac{V_m \sin(\omega t + \theta)}{R_1} + \frac{N (\phi_2 - \phi_1)}{R_1}
\end{align*}
\]

(3.7-16) (3.7-17)

The matrix of structural equations is given as

\[
\begin{array}{cccccccc}
V_m & V & \phi_m & \phi_0 & \phi_1 & \phi_2 & \phi_1 & \phi_2 & i_1 & i_2 \\
1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\
2 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\
3 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\
4 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\
5 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\
6 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\
\end{array}
\]

FIG 3.10 : THE MATRIX OF STRUCTURAL EQUATIONS

The interpretation of this causal structure is that applied voltages produce magnetic flux in the windings of the core which further induce current in the circuit. Due to the applied voltages also current is produced. The total current in the input and output circuits is as given by equations (3.7-16) and (3.7-17).

FIG 3.11 : THE CAUSAL STRUCTURE OF THE MAGNETIC AMPLIFIER
3.8 CONCLUSION

The intuitive appeal of the qualitative variable as a primitive of human knowledge based reasoning is almost undeniable. Reduction of unnecessary detail and emergence of the relevant behaviour of the system are properties of QM. However, it is desirable to develop QS techniques which permit a more detailed description of quantities and functional relationships than existing qualitative reasoners. Moreover to allow effective and efficient model based reasoning tasks to be performed, neither the precision of real numbers nor exact and complex relations between variables are required. Also, a technique which can qualitatively generate a physical system's behaviour in terms of its state sequence with associated temporal durations will enhance the viability for real applications of such approaches.

In this work, FQS technique has been adopted to overcome the limitations of qualitative reasoning techniques. Fuzzy sets allow commonsense knowledge to be included in the interpretation of values by using membership grades. This technique has strength as well as sign information on functional relationships among variables. Strength and sign information considerably reduces the inherent ambiguity of qualitative calculi. The temporal duration can also be measured as explained in chapter 5. The spurious behaviours generated by this techniques are prioritised according to their ranks. The technique has been discussed in detail in the next two chapters.