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1 Introduction

1.1 *Brief Summary*

This document is the latest version of a roadmap for model-based systems and qualitative reasoning (MBS&QR) produced by the MONET Network. It contains a set of ambitious domain-based technological visions. These visions provide an important driver for research in MBS&QR. Firstly, they challenge researchers in a variety of domains to strive for exciting and useful goals. Secondly, they show how model-based and qualitative reasoning can assist in attaining those goals. Thirdly, they provide a practical focus for assessing current research in model-based and qualitative reasoning, and the technological needs identified in a previous version of the roadmap are prioritised based on this assessment.

1.2 *Background*

MONET is the European Network of Excellence in Model-based Systems and Qualitative Reasoning. In 1998, it produced two versions of a roadmap for the technologies covered by the Network. A third version of the document was produced in 2003, attempting to identify the likely commercial development of the technology, and the improvements to the technology needed to achieve the expected industrial development. It is available from the MONET web site *http://monet.aber.ac.uk*.

The first and second MONET roadmaps attempted to map possible applications of the technology against time. The third roadmap took a different approach. The MONET2 Network of Excellence concentrates on four areas of application of model-based and qualitative reasoning (automotive, applied diagnostics, biomedical, and educational applications). A roadmap has been produced for each of the application areas, examining technology drivers in that application area, and matching them to the capability of model-based reasoning systems. The roadmaps for the individual application areas have identified technological barriers to applications of model-based reasoning. The third roadmap collected and collated those technological issues, presenting them in a more logical order.

1.3 *Content of this Document*

This fourth version of the roadmap extends the approach taken in the third roadmap. It contains much of the technological detail of the third version, but is more targeted in the following ways:

- *Key ideas*: A brief summary is given of the most important ideas in the area of the Network.
- *Examples*: Material has been added showing the benefits provided by model-based and qualitative systems over other choices for system building.
- *Longer-term vision*: A range of examples are explored that show where the technology will be needed for the systems that we will want to build in ten years time.
- *Prioritisation of technologies*: The technological barriers identified and categorised in the third roadmap are rearranged and presented in order of their necessity for the visions of technological applications given in the previous section.

2 Model-based Systems Technology and Methodology

2.1 Example Application - Remote Diagnosis and Repair

2.1.1 Remote Agent (NASA)

Part of the *New Millennium Program* (NMP), the RA (*Remote Agent*) was the reference for autonomous spacecraft software architecture. Starting in 1995, scientists and engineers at JPL and ARC developed an architecture for the autonomous control of a satellite.

The RA was clearly the result of an integrated model-based approach to solve numerous problems related to autonomy. *Immobots* (standing for immobile robots) share the need for autonomy of widely distributed systems with numerous transducers. The idea, still futurist, but nonetheless relevant is that these immobots will have to regulate and control their own internal functions in a precise and robust manner. This of course requires a precise coordination between the high layers of the software, based on symbolic reasoning techniques and the low level autonomous processes based on techniques from Control theory.

DS-1 (*Deep-Space I*) was the first spacecraft utilising these ideas and was launched in 1998. Successful tests (known as RAX for *Remote Agent eXperiment*) were conducted in May 1999.

Diagnosis and recovery are performed on board by the RA, based on real-time acquisition of observations from sensors. A specific RA module, called MIR (*Model-based Identification and Reconfiguration,* also called *Livingstone*) is entirely dedicated to the task of identifying the state of the satellite's equipment, detecting faults and proposing reconfiguration actions [Williams and Nayak, 1996, 1997]. Williams and Nayak describe an original framework for a high level description of complex physical systems. Each component is described by making use of probabilised discrete transition systems that represent the possible changes between their operating modes. The behaviour of the component in each of these modes is described by making use of simple qualitative constraints in propositional logic.

The advantages of this high level qualitative modelling are several:

- The framework is generic enough to be used to represent all the equipment on-board the satellite, from software drivers to sensors, electronics and AOCS (Attitude and Orbit Control Systems)
- The model development doesn't require complex behaviour descriptions of equipment
- The formalism is modular and models can be easily reused and assembled

MI (Mode Identification) uses two major algorithms, one to reason on constraints describing the component behaviours in every mode and based on enhanced algorithms of Truth Maintenance Techniques [Williams and Nayak, 1997], another performing a search for the set of most probable states given observations at each time step, and known as 'best first search' in AI [Williams and Nayak 1996]. MR (Mode Reconfiguration) takes in a set of reconfiguration goals and uses the model of the satellite to infer a minimal cost target set of states consistent with the required goals. This was the first viable autonomous reconfiguration system in AI and presented numerous advantages over other techniques. The key points of this achievement were:

- The complexity of the diagnosis is strongly reduced by enhanced algorithms
- The modelling is performed at a qualitative level
- MR uses the same algorithms as MI
- MR is reactive and able to work in real-time

2.1.2 The European Experience: the KOALA Approach (LAAS / LIPN / CNES / ASTRIUM)

The NASA experience and the advantages that could arise from more autonomy mean that there is an increasing level of attention to the autonomy issue from European space organisations. In particular, CNES has undertaken an exploratory development program on autonomy (*DE Autonomie*) whose goal is to analyse the feasibility and advantages (technological as well as economical) of autonomous satellites. This program, started in 1998, includes the development of an autonomous satellite ground based prototype. Within "DE Autonomie", a state of the art study in the area of Diagnosis and Decision Support was performed in 1999 [Travé-Massuyès and Dague, 1999a and 1999b). Also in the framework of the "DE Autonomie", a project was initiated by CNES at the end of 1999. This project involved collaboration between two research labs LAAS and LIPN, as well as CNES and ASTRIUM. It aimed at building an on-board diagnosis and reconfiguration system for autonomous satellites.

The starting point of the work was the results published by NASA in 1996 and 1997. The aim was to show that the qualitative formalism could be complemented by continuous models when necessary and that fast diagnosis was still possible even in the case of a larger number of components. The modelling framework hence fell into the hybrid modelling paradigm. One of the motivations for a hybrid approach came from the fact that monitors discretizing the sensor data into qualitative knowledge are difficult to design by hand and that some very precise information that is currently available to engineers working on satellite control is lost in the process of abstracting the model of all components. Problems which arise from only having qualitative models are:

- The triggering of numerous false alarms
- The difficult evaluation of threshold values
- The availability only of rough models
- The inability to focus diagnosis accurately

These are the reasons why the work concentrated on inserting techniques for continuous systems fault detection and isolation, already developed at LAAS, namely the Ca-En system [Travé-Massuyès and Milne, 1997] into the existing high level qualitative diagnosis system. Based on this hybrid formalism, a new set of algorithms, which interleave the search for the most probable diagnoses with consistency checking were defined and implemented in the KOALA software prototype (http://juban.free.fr/projects/koaweb/koala.html) [Bénazéra and Travé-Massuyès, 2003] [Bénazéra 2003].

It is foreseen that this work will be carried on in two directions:

- An evaluation of MBD approaches on a case study proposed by Alcatel Space.
- A validation of the KOALA approach on an autonomous satellite test bench at CNES.

2.2 *Key Ideas of Model-based Reasoning*

Model-based reasoning and qualitative models are central to the kind of work given in the example above. This section explores the key ideas behind model-based reasoning and why qualitative reasoning is foundational to achieving the types of results discussed.

2.2.1 Separation of System Model from Problem Solving

Model-based systems are based on a separation of the problem solving algorithm from the model of the domain. Once a library of appropriate component models has been established, only a structural description of the respective device (e.g. obtained from design data) is required to automatically generate a system model and based on it, a problem solving system dedicated to this device. Figure 1 illustrates this idea for the production of a model-based diagnostic system.

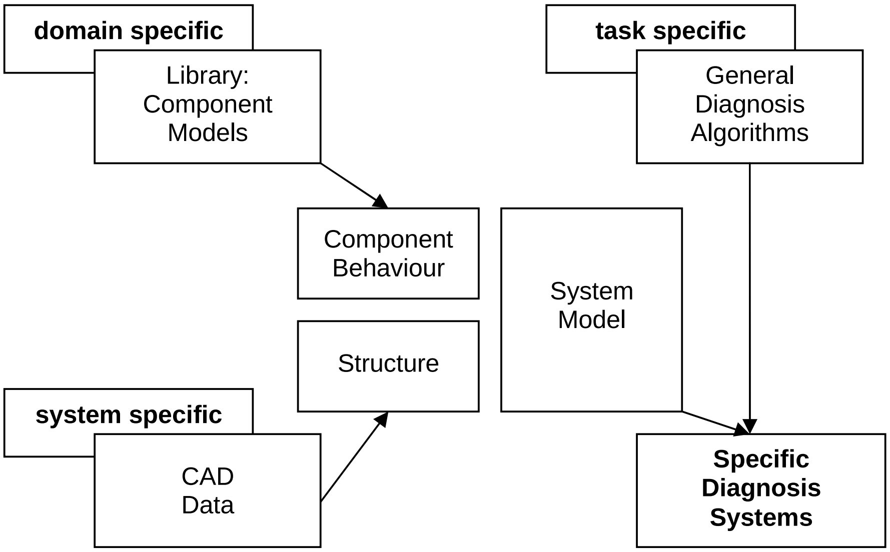

Figure 1: Automated Generation of Model-based Diagnostic Systems

2.2.2 Compositionality

Since systems are assembled from standard components and the behaviour (and misbehaviour in the case of a fault) emerges from the behaviour of these components, establishing a model library is feasible and entails collecting models of (correct and faulty) behaviour of such standard components. This is important: this kind of model-based reasoning cannot be performed if the overall behaviour of the system cannot be composed from the behaviour of the components and the way in which they are linked. Where there is compositionality of models, a high degree of reuse is possible, as well as prediction of what will happen in unexpected circumstances such as failure situations.

2.2.3 Existence of Different Abstract Problem Solvers

Section 3.3 gives a wide range of possible problems that can be solved in a model-based way, where solving a new problem involves fitting a different appropriate kind of model into the generic problem solver.

2.2.4 Modelling at Different Levels of Abstraction

In diagnosis, for example, modelling different kinds of problems may well involve modelling different phenomena and at different levels of detail. However, while there may be a need for quantitative and or semi-quantitative models, qualitative models provide a nice solution to represent phenomena at a higher level of abstraction.

2.3 Importance of Qualitative Reasoning

Engineers generally work with numerical models, but in this type of work the capability to exploit qualitative models [Forbus 88] turns out to be crucial for several fundamental reasons:

- In particular in early design phases, only a partial specification of components and parameters is available, which prevents the use of numerical techniques.
- Many tasks, such as FMEA or the generation of diagnostic manuals, aim at statements about classes of (fault) behaviour and of symptoms rather than specific instances. For example, the effect of a leakage of any size has to be predicted, rather than just a leakage of a specified size.
- Faults are defined as qualitative deviations from normal functioning (e.g. flow through pipe is reduced), rather than arbitrary discrepancies with respect to precise values (e.g. flow is 4.12 gallons/minute, but should be 6.73 gallons/minute).
- Precise values often do not exist, for example because the vehicle is operated in a noisy and widely unmeasurable environment, and only incomplete data is available (e.g. about properties of the road surface).
- Qualitative models provide an appropriate level of abstraction for modelling complex systems and processes where standard mathematical models do not exist or are not tractable (consider the combustion process or communication among the control units).
- They enable an intuitive representation and presentation of knowledge and information to the users.
- Where more detailed models are needed in order to produce precise answers, the qualitative models provide a way of focusing the numerical modelling on the answers that are needed.

The qualities outlined above mean that qualitative models often provide appropriate answers for a wide range of systems with incomplete knowledge. This enables automation of reasoning about the complex systems found in modern machines, early identification of safety and reliability issues, and generation of good diagnostics. This can be done for many different system variants with little extra effort.

3 Uses of Model-based Reasoning

The previous section has illustrated that combining compositional models of a domain with domain independent problem solvers can produce model-based systems that are able to reason about different versions of a product, or about a process as its operating state changes, and that qualitative modelling is an important constituent in building such systems.

This section considers why model-based reasoning is useful for real world applications, and what kinds of application can be built using it. The consideration of the usefulness of model-based reasoning is split into two parts - consideration of the use of model-based reasoning for complex systems, and the contribution of qualitative reasoning to model-based systems. Model-based reasoning can ameliorate the problems of working with complex systems, because it provides a structure for reasoning about such systems at appropriate levels. Qualitative reasoning provides a significant contribution to model-based systems, because it can be used to focus numerical reasoning, and to interpret the results of numerical reasoning.

3.1 *Dealing with Complexity and Change through Model-based Reasoning*

The automotive industry provides an excellent case study for the utility of model-based reasoning. On the one hand, the complexity and sophistication of vehicles is growing, and so it is becoming harder to predict interactions between vehicle systems, especially when failures occur. On the other hand, legal regulations and the demand for safety impose strong requirements on the detection and identification of faults and the prevention of their effects on the environment or dangerous situations for passengers and other people. Also, customer satisfaction is important in order to remain competitive, and means that the manufacturer must eliminate break-downs and reduce maintenance time and the number of misdiagnoses.

In addition, cars come in many variations of details and supplements, dependent on the make, year, or even almost individual customization (this problem is also relevant to suppliers delivering functionally similar subsystems to different manufacturers or for different models). This issue, termed the *variant problem*, is a major cost factor, multiplying the efforts dedicated to different diagnosis-related work processes.

Performing separate design analysis and diagnostic code generation for every variant has become prohibitively expensive. Model-based reasoning provides a solid basis for the horizontal integration of different work processes that have been disparate in the past. [Struss and Price, 2003] shows the capabilities of model-based reasoning in that domain, and highlights the breadth of effort that automotive manufacturers are putting into this technology.

3.2 *Why and How Qualitative Models Complement Numeric and Black-box Type Models*

The need to represent physical systems by models is common to all scientific and engineering domains. But the modelling process encounters difficulties from both ends: a model must adapt to the knowledge available and to the task it is built for. The possible limitations of traditional numeric methods with respect to these problems mean qualitative models can be a good alternative, or a complement to the information provided by numerical modelling:

- Qualitative models cope with uncertain and incomplete knowledge;
- In order to cover all possibilities within a state space, a numerical model will need to be run a significant number of times. A qualitative model can predict the same possible outputs at once in compact form;
- The qualitative predictions provide the relevant qualitative distinctions in the system's behaviour;

- The modelling primitives allow for a more intuitive interpretation.

A system’s evolution may be as well tackled in discrete terms, by defining states and events that trigger transitions between states. This is generally the adopted point of view when continuous dynamics of behaviour are not relevant. The important contribution of QR is to provide an intermediate level between discrete event and continuous models, in which the state space is discretized into a number of finite states, and transitions between those states obey continuity constraints.

The ultimate goal in modelling would be to be able to represent a system in an integrated manner even though the details of the system may be known unequally. Such a goal could only be reached by a system able to make use of the various existing modelling paradigms. Indeed, complex systems are characterized by heterogeneity of their components: a continuous behaviour component may be controlled by a valve including a commanding mechanism (driver), and the valve driver is all logic, and so such a mixture of levels of modelling is quite typical for complex systems.

Three types of alternative approaches have been proposed towards achieving such a goal. They have each been shown to be powerful and can be seen as contributions towards this *unified modelling view*:

- Use more qualitative and quantitative information, as is done in the semi-quantitative simulation approach. Attempts at such an approach include
  - quantitative extensions of QSIM like Q2 and Q3 which preserve the underlying qualitative model
  - interval model-based simulation
- Utilise results in the area of systems theory, like the qualitative phase space analysis approach.
- Integrate QR with traditional engineering modelling approaches like numerical simulation or system identification. Self-explanatory simulation and hybrid systems domains exemplify the first type of integration of these things, and the second is explored in the next paragraph.

In the system identification approach, QR complements numerical identification approaches and can play a crucial part in structural identification, i.e. in selecting the equation form within the model space. QR techniques naturally complement grey box and black box system identification techniques: in one case, they allow us either to supply the necessary knowledge or to emulate the expert's reasoning about structural identification; in the other, when the box is not completely black, as is quite often the case, they allow us to easily choose the proper equation complexity but above all to embed a priori knowledge with a significant gain in model robustness.

Another important fact is that QR models complement engineering models by their conceptual nature and higher level of abstraction. They bring in new features, such as the underlying causality, that are crucial for supporting reasoning mechanisms.

Numerical models have poor background for logical and causal reasoning. Hybrid model-based systems proposed recently have clearly shown that QR concepts establish a necessary link between numerical continuous models and the logical reasoning level (cf. NASA work and LAAS work). This also appears to be clear when comparing work on diagnosis from the FDI community, which is engineering grounded, and the DX community. The models used by the FDI community, mainly sets of differential equations in matrix form, and the algebraic manipulations that are applied, do not enable traceable predictions and do not include the necessary attached labels for allowing logical reasoning. The use of QR concepts, for example the underlying causal influences employed in Ca-En, makes these engineering models suitable for supporting logical reasoning.

A clear example of the need for qualitative models comes in the diagnosis domain. More often than not, even when numeric models of normal behaviour are available, fault models are not available, and neither is the data that would be necessary to derive numerical fault models available. In this case, qualitative models are an obvious solution: they are good at capturing the uncertainty related to faults and they are generally sufficient for diagnosis purposes.

3.3 Examples of MBS&QR Today and What it is Used for

The following section gives an idea of the breadth of applications for which model-based reasoning is currently being used. It can be seen that this is already a technology with a wide range of applicability and a good deal of value for those who apply it.

Fault detection by model-based prediction: numeric and non-numeric
If one knows what values the system parameters should have, then one can detect faults by seeing if the system is producing these values or not. But for many systems, the behaviour of the components and sub-systems is not well enough known to be used for a numerical simulation. In this case, qualitative reasoning and simulation can be used to produce a description of the overall expected system behaviour, thus enabling fault detection [Travé-Massuyès and Milne, 1997; Bénazéra, Travé-Massuyès, Dague, 2002; Bénazéra and Travé-Massuyès, 2003].

System simulation before the real system is built, such as satellite design, or virtual prototyping of vehicles
The developers want to understand what the system will be like, but it won’t be physically constructed for some time. Complex products involving discrete and process sub systems are very difficult to model with traditional simulation systems, but the qualitative nature of the behaviour of the system can be determined with qualitative simulation [Bénazéra and Travé-Massuyès, 2003; Ward and Price 2001].

Process understanding and monitoring
Operational plants don’t run complex numerical simulations all the time, but the operators still need to know if the plant is reacting as it should, for example, temperatures increasing and decreasing when they should be. In addition, the numerical simulation creates a complex set of numbers when the user really wants to understand that the key system parameters are increasing or decreasing. Qualitative reasoning, on the other hand, can provide an appropriate level of reasoning [Adam and Grant, 2001; Trelease and Park, 1996].

Explanation of numerical simulations
Numerical simulators produce a battery of numbers, but not the easy to understand description of system behaviour the user is looking for. Qualitative reasoning can extract the system’s qualitative behaviours from the simulation output, enabling a comprehensible explanation for the user [Forbus and Falkenheiner, 1991; Price, 1998].

Compositional Model-based diagnosis and state tracking
By linking together a collection of component descriptions, diagnosis can be performed on the whole system, and the state of the system can be tracked over time. This is much faster and requires less man effort that traditional manual design and analysis approaches [Dvorak and Kuipers 1991; Struss and Price, 2003].

Model-based systems provide many opportunities for re-usability
Once the model-based description of a component is created, it can be used in many system configurations. Model-based systems build system descriptions from the composition of many sub models, the key to this reusability [Struss and Price, 2003].

Variants problem

Current approaches have a high cost of developing diagnostics as the sub-systems change. These variants are desirable, but too expensive to support. A model-based system automatically generating the diagnosis makes this practical and hence opens up a whole new area of commercial opportunity. The automotive area is a prime example. [Struss and Price, 2003]

FMEA generated from the design description and component models

Automatically generating the Failure Modes and Effect Analysis (FMEA) from the design description of an automobile's electrical system saves considerable man effort and is more accurate. Automated sneak analysis has identified problems not previously detected, for example. Model based FMEA is now a standard module offered by design company Mentor Graphics [Struss and Price, 2003].

QR models in the educational context

Qualitative reasoning can be used to simulate systems for students so that they can understand the errors they have made and how a system should function [Bredeweg and Forbus, 2003].

QR to help decision making under uncertainty

In marketing, the knowledge is imprecise and often unknown. For example, evaluation of credit risk of companies and classifying the profiles of consumers call for qualitative descriptors. QR can be used where numerical approaches are not applicable [Flores et al, 2001]

At present, the models used in model-based systems need to be coded specifically for the intended task, albeit in a reusable, compositional way. The ideal state would be to have a general modelling capability that can be applied to many different tasks.

The present state of the technology allows the modelling of a system at different levels of granularity, but switching between the different levels and identifying the appropriate level at which to reason in order to solve a specific problem cannot be achieved easily in the general case.

4 Ten Year Visions for Model-based Technology

This section presents a range of exciting potential applications that are beyond what we are capable of at present, and which depend on model-based reasoning for successful execution. The presentation of these as ‘ten year visions’ is somewhat arbitrary. While none of them will be fully realised in less than ten years, it would take a strong concentration of funding and effort to complete them within that time, and so the likelihood is that the visions will take longer than that to come to fruition. The visions highlighted in this section are:

- The Science-bot: automated education
- Virtual vehicles: from conception to recycling
- Understanding and managing complex natural systems
- Interpretation of 4D medical data
- Robust autonomous problem solvers in the face of uncertain situations

4.1 The Science-bot: Automated Education

> *Scenario:*
> A science-bot is an interactive agent that is knowledgeable about a set of topics in science. Each science-bot is specialised in its own area of expertise. It will have considerable amounts of domain knowledge and be able to assist learners in helping them to acquire knowledge, understanding and awareness. Science-bots will recognise and know the informational needs of their learners and users and adjust the communicative interaction so it is appropriate to the specific user. Additionally, they will have their own teaching and communication goals depending on the circumstances in which they have been placed. Specifically science-bots will be able to discuss topics from multiple perspectives, explain phenomena and criticise ideas and thoughts presented to them.

Tutoring and training was one of the earliest applications of model-based reasoning, e.g. [Brown et al. 1982; Hollan et al. 1984; Wenger 1987]. Presently there are several types of model-based tools available for use in educational settings. Examples of these typically take the form of model-building environments (using the idea of ‘learning by knowledge articulation’) and interactive simulations, and they deal with a variety of issues. For surveys of qualitative reasoning and education, see for example [Forbus, 1996; Bredeweg and Winkels, 1998; Bredeweg and Forbus, 2003].

Model-based Systems and Qualitative Reasoning technology is of great importance for developing, strengthening and further improving education and training on topics dealing with systems and their behaviours. Educators and learners need the means to capture and share conceptual knowledge. That is, means to formally represent (and automate reasoning with) knowledge that is qualitative, incomplete, fuzzy and uncertain, and in communicative interactions frequently expressed verbally and diagrammatically. Not being able to sufficiently represent this knowledge in a computer-processable format, preserving its unique characteristic, hampers the sharing and communication of insights and theoretical developments. This is particularly a problem in education and training situations. QR technology can provide computer-based facilities to represent and reason with this kind of conceptual knowledge. However, MBS&QR technology is not well known to a wider audience and there are currently not many ready to use products and tools available to exploit the capabilities of this technology. As result, the full potential of qualitative models as a key component of tutoring systems and interactive learning environments is still to be established.

We envision that the following products can and should be developed in order to address the need for educational software dealing with learning about systems and their behaviour. *Interactive articulation devices* are model building environments that allow learners to articulate knowledge (conceptual models) and by doing so learn about a domain. Learning by modelling using traditional approaches has been shown to be effective for enhancing student understanding, but is often hampered by the mathematical complexity of knowledge representations and the lack of means to represent causal knowledge. QR has the capacity to overcome these hurdles. Based on MBS&QR technology, tools can be developed that will allow diagrammatic sketching of ideas and conceptual knowledge and, have this automatically transformed into simulations. In order to be effective, such environments should also have the means to criticise models and simulations, and help learners with de-bugging them.

The concept of *autonomous science-bots* further advances the idea of individualized support, by the building of resources of previously defined models / model parts and coaching. Science-bots focus on knowledge transfer related to institution-defined goals (where the institution might be a university or school etc.).

Autonomous training-bots are a special class of science-bots. They focus less on knowledge transfer related to institution (universities, schools, etc.) defined learning goals. Instead they operate side-by-side with workers (for instance, in factories or business oriented environments) providing online help and also support for these workers with performing their tasks. MBS&QR technology can provide to the basis for developing such a tools.

4.2 The Virtual Car from Conception to Recycling

> *Scenario:*
> Vehicle manufacturers and their suppliers face increasingly serious challenges. The complexity and sophistication of vehicles is growing, and so it is becoming harder to predict interactions between vehicle systems, especially when failures occur. Legal regulations and the demand for safety also impose strong requirements on the detection and identification of faults and the prevention of their effects on the environment or dangerous situations for passengers and other people. Finally, customer satisfaction is important in order to remain competitive, and means that the manufacturer must minimise break-downs and reduce maintenance time and the number of misdiagnoses.

The cost of meeting these challenges for a new vehicle model has increased over time, and is demanding both in terms of manpower and elapsed time. In response, vehicle manufacturers have gradually moved towards virtual prototyping and automated analysis. Virtual prototyping implies using software to construct a model of a system, and testing the model works correctly, thereby reducing the need for actual prototyping. Automated analysis means having software performing analysis – for example, failure modes and effects analysis – so that the engineers need to spend less time analysing the system.

The logical end point of this activity is the virtual vehicle – a model of the complete vehicle that can be developed and used throughout the lifetime of the vehicle. When the decision to make a new vehicle is taken, then the requirements can be used to build a functional model of what the vehicle will be required to do. This might allow automatic specification of much of the complex equipment in the vehicle. As the design is fleshed out by the engineers, either stipulating physical components or specifying the aesthetic aspects of the vehicle (which will constrain design choices), then the extra information should be incorporated into the model of the vehicle from databases of component models. As enough information becomes available, it will be possible to perform model-based tasks of the type described in section 3.3 – failure modes and effects analysis, system simulation, diagnosability analysis, production of diagnostics, generation of control software. As variants of the new vehicle design are produced, all this work can be repeated with much less effort, reusing all information that can be used from the original model. When the vehicle is finally disposed of, the virtual vehicle can be used to plan disassembly and efficient disposal of materials.

Model-based reasoning is a vital component of the virtual vehicle. The use of compositional models makes it possible to automate the repeated reasoning on a design which is necessary for this kind of work. In particular, qualitative reasoning has an important contribution in enabling early analysis before all information is available, and also in focusing numerical reasoning to obtain more specific results. One issue that will become more important is the ability to reason as effectively as possible about a system where different subsystems are specified with different degrees of detail – perhaps only a qualitative model exists for one subsystem, a functional model for several others while one or two subsystems can provide detailed numerical models. This is not possible at present, but will become vital if the virtual car is to be realized.

4.3 Understanding and Managing Complex Natural Systems

> *Scenario:*
> We wish to understand the germination dynamics of the spores of fungal pathogens, such as for example the oospores of *Plasmopara viticola*, in response to both endogenous factors, either metabolic (e.g. the influence of the calcium ion) or genetic, and to exogenous factors due to the climate (e.g water availability) and environment on the germination process. A deep comprehension of such complex interactions is essential for a rational and optimized treatment planning of plants with a consequent benefit for the health of both consumers and operators, and for the impact on the ecosystem. The available pathophysiological knowledge on the endogenous mechanisms at work is highly incomplete and qualitative whereas the exogenous factors can be completely and quantitatively known (under laboratory conditions). Moreover, the mechanisms involved may occur at different time scales. There is the need for the development of proper QR-based modelling methods that are capable of dealing with different levels of knowledge, and even more important, with different time scales.

Models of the dynamics of natural systems offer potential benefits to the deep comprehension of the system under study as well as to the performance of specific tasks. The dynamics of such systems result from complex interacting mechanisms, and are very often regulated by both endogenous and exogenous factors. Unfortunately, the available knowledge of the underlying mechanisms is very often highly incomplete, and identifying mechanisms with quantitative methods is a challenging prospect. This makes the modelling problem quite hard to be solved, and even unsolvable when, as can occur for natural systems, the available observational data set is inadequate.

QR methods properly integrated with quantitative methods could overcome the identification problems outlined above. An example of a successful application of a QR-based hybrid method to solve serious identification problems deals with the identification of the intracellular Thiamine (vitamin B1) kinetics in intestinal tissue [Bellazzi et al, 2001], the understanding of which is quite important as Thiamine is one of the basic micronutrients present in food and essential for health. It participates in carbohydrate metabolism, in the central and peripheral nerve cell function, and in myocardial function, and its deficiency causes beriberi with peripheral neurologic, cerebral and cardiovascular manifestations.

4.4 Interpretation of 4D Medical Data

> *Scenario:*
> One of the most stimulating application domains where QR can fruitfully support traditional quantitative techniques in the investigation and comprehension of complex phenomena is Electrocardiology. In present clinical practice, information about the heart electrical activity is routinely gathered through Electrocardiographs (ECG's), which record electrical potential from just nine sites on the body surface. However, thanks to the latest technological advances, body surface potential maps are becoming available, as well as epicardial maps obtained non-invasively from body surface data through

> mathematical model-based reconstruction methods. This 3D data is gathered over time, giving a 4D data set. Electrocardiographic maps can capture a number of electrical conduction pathologies (arrythmias, Wolf Parkinson White syndrome, to cite just two) that can be missed by ECG's analysis. But the interpretation of such maps requires skills that are possessed by very few experts.

An important role in the process of defining an interpretative rationale for electrocardio-graphic maps can be played by QR methodologies for spatial / temporal reasoning that could (i) support the expert in identifying salient features in the map, and (ii) achieve the long term goal of automating map interpretation to be used in a clinical context. QR approaches based on spatial aggregation may be used to identify patterns and salient features in epicardial activation isochronal maps [Ironi and Tentoni, 2003a]. In this kind of map, the time at which each point starts activating, derived from the electrical data of a whole heart beat, is visualized by means of isocurves. A lot of information about the excitation wavefront structure and propagation is summarized in a single such map, since isocurves represent subsequent snapshots of the travelling wavefront.

Breakthroughs location, high and low velocity pathways, conduction block regions, for example, are salient features that characterize the heart electrical activity: they visually correspond to specific geometric patterns to be identified in the map, such as minima location, maximum and minimum elongation directions in the isocurves shapes.

Spatial aggregation approaches, designed for the interpretation of numeric fields that are spatially represented and capable of identify global patterns and capturing structural information about the underlying events, exist in literature. But, such methods just consider 2D geometrical domains that can be discretized by a uniform meshes. But, given the complexity of the geometry of the heart (3D and non uniform meshes), such methods are not applicable to the interpretation of cardiac maps, and therefore there is the need for the development of methods capable of dealing with 3D complex geometries over time.

Besides helping medical research in the important phase of the definition of interpretative rationales through models and their simulation, QR methods can lead to the automated interpretation of numerical fields in specific medical domains, and therefore to the realization of tools that can eventually enter the clinical practice.

4.5 Robust Autonomous Problem Solvers in the Face of Uncertain Situations

> *Scenario 1:*
> Satellite systems need to make decisions no matter what information is available.
> A satellite system has constructed a plan of how to achieve its goals. However, the key infrared sensor is not responding. Using its Model-based System, a new plan is constructed. It then uses a qualitative simulation to verify that the plan meets the goals. The simulation also generates expectations which can be used to monitor the execution of the plan to detect problems. The satellite executes its plan, matching sensory data to measurements and completes the mission.
>
> *Scenario 2:*
> An autonomous planetary rover, comparing its limited sensory data to a prediction of the sensor readings detects an inconsistency as it moves down the side of a shallow crater. It uses a Model-based System composed of models of each component to determine that a component has failed. Even if a sensor is lost; it needs to plan what it will do to complete the mission. It then reconfigures itself and re-plans the mission with its new system structure. Its sensory data now matches the predictions of its Model-based System and it reaches the crater floor to continue its explorations.

These are two situations where autonomous decision making is needed by a system. There are others outside of the planetary exploration domain, for example, robots in hostile environments, or building maintenance systems where a human supervisor is not continually present.

Autonomy requires a global perception - state identification - action loop, which is essential to provide the system with adaptable behaviour to face unknown events. Fault Detection Identification and Reconfiguration (FDIR) involves a set of functions, which are obviously crucial to adaptability.

Model-based diagnosis (MBD) techniques would benefit the overall spacecraft and constellation design process. These tools indeed provide an integrated development framework able to produce easily the equivalent to the currently used on-board FDI systems and providing substantial additional benefits from the development step to the operation step:

- the FDI design will be easier to build, reusable and more generic when based on MBD
- MBD enables a global and unified management of the equipment and functional levels
- the models can provide support for validation
- MBD should lead to a decreased level of false alarms by making maximum use of redundancies and numerous non-telemeasured on-board observations
- MBD should be able to automatically handle more situations than the current FDI systems, avoiding the satellite or constellation to transit to ‘safe mode’ (i.e. dead position, panels facing the Sun) and consequently increasing availability

Techniques for autonomy will offer new possibilities for the development of spacecraft missions by helping engineers automatically produce a large part of the ground and on-board software as well as a great help for the hardware specification and the design of the most useful on-board sensors and telemeasures. Space engineers should be able to produce more complex constellations and spacecrafts for difficult exploration or critical missions.

5 Technical Challenges

This section attempts to prioritise the development of further technology in this area according to the needs of the visions presented in section 4, and the experience of the roadmapping team in attempting to deploy these technologies.

One issue which will not be dealt with any further in this section is the one of cross-discipline research. While we believe that MBS&QR have a key contribution to make to the realization of the visions in section 4, they are not MBS&QR problems per se. The Science-bot, for example, will also need advances in analogical reasoning and user modelling, in order to be able to work in the way that is outlined.

Version 3 of the roadmap classified and discussed a wide range of MBS&QR related technological work, and it is still available from the MONET web site if you are interested in seeing the full breadth of work that is considered interesting and potentially useful. It has longer descriptions than the ones given in this document, and so version 3 should also be consulted for more detail of what is discussed here.

In the following sections, the most important of the technologies for developing commercial products from MBS&QR are ordered by importance as vital or important.

5.1 Vital Technologies

These technologies are needed in order for MBS&QR to achieve widespread successes, as opposed to the targeted breakthroughs that have been achieved so far.

- Models of complex systems
- QR methods using more sophisticated mathematics
- Integration of models from different domains

5.1.1 Models of Complex Systems

This is a particular acute issue: many important real world applications fit this description, and continued improvements in this area should lead to adoption of model-based techniques for many applications.

What the Problem is
Many of the processes that we are modelling evolve over time, happen in a particular space, and are impossible to specify completely as not all relevant parameters can be determined (giving rise to uncertainty). In addition, lack of precise data makes it impossible to describe the system quantitatively. Many real-world systems are very complex; and while the exact nature of the complexity varies from system to system, the contributors to the degree of complexity are: non-linearity, order, dimensionality, degree of coupling and non-determinism.

Examples of such systems are:
- Human brain, cardiovascular system
- Macro-economic systems
- Chemical process plant

State of the Art
A great deal of work has already been done in the engineering disciplines, but such work often relies on the availability of quantitative models. Model-based and qualitative reasoning methods exist to deal with situations where such quantitative models are not available, but are normally restricted to

one aspect, such as dynamic behaviour, of a problem. They cannot combine various modalities, such as time, space and uncertainty, which may be needed for modelling the real world. In addition, the expressive power of many qualitative methods is restricted in the sense that even within one modality not all required behaviour can be modelled. In addition, many of the available methods do not scale up to real-world models.

Some examples of past and present approaches to dealing with the various aspects of complexity are:

Quantitative Modelling

- Identifying types of non-linearity (e.g. Michaelis-Mentin, Product, Power)
- Coupled system analysis – for loosely and tightly coupled systems
- Partial differential equations to deal with dimensionality
- Perturbation analysis to handle systems operating on different timescales (stiff systems)

Qualitative Reasoning

- Generalising linear / non-linear models
- Function free estimation (via fuzzy quantity spaces)
- Time scale abstraction (matches perturbation analysis)

In addition there are a number of approaches to categorising models which enable the identification of types of complexity:

- Model categorisation on the basis of model properties
- Multimodelling on tetrahedron of state (includes functional)

What Further Research is Needed

More powerful modelling languages:

- Allowing levels of abstraction in languages describing temporal processes
- Languages for the description of uncertain evolution of processes, possibly of a qualitative nature
- Integration of various modalities into the same language

Coupling of models:

- Development of tools to integrate types of complexity in appropriate models at varying levels of abstraction
- Modelling complexity by various means: simplification, abstraction, etc.

Extended definition of a space of models from which desired model can be selected.

- Partial models
- Integrated co-operative models dealing with single, or a small number of aspects of complexity
- Model definition framework
- Strategies for co-operative use

5.1.2 QR Methods Using More Sophisticated Mathematics

What the Problem is

In many cases, methods from model-based systems and qualitative reasoning build upon existing mathematical methods from calculus (e.g. differential equations), algebra (equations, functions and sets), and logic. The basic methods are geared towards the area of model-based systems and qualitative reasoning: (1) by restricting the domains and co-domains of functions to be discrete, possibly ordered, instead of being continuous, and the results are then still consistent with the underlying axioms, (2) by adding task-specific problem solving methods, such as methods for diagnosis, which are able to act on particular representations in a particular fashion. There are many mathematical methods which are restricted in their practical usefulness as qualitative versions of those are as yet not available.

Examples:

- In the area of uncertainty reasoning, when data are not available or scarce, it is not possible to quantify a probability distribution reliably (this is because you can still use subjective estimates)
- In economics, structural equation models expect quantitative information, and the present state of qualitative mathematics is unable to deal with them

State of the Art

The theory underlying current model-based and qualitative reasoning systems is already firmly grounded on logic (e.g. logical abduction in abductive diagnosis and consistency checking and assumption-based reasoning in consistency-based diagnosis), algebra and calculus (e.g. QSIM). However, there are many open ends in this work, as the expressive power of the languages used for modelling is often restricted. For example, even though it is possible to provide a formal specification of dynamic behaviour in a qualitative fashion, it is as yet not possible to specify the uncertainties regarding these behaviours qualitatively in a probabilistic framework, as the mathematics to do so is still not powerful enough. Work going on in constraint logic programming can be taken as a starting point. With the exception of situations where uncertainty is involved where qualitative probabilistic networks can be taken. In both areas much progress has been made in the last three years, which can be usually exploited in MBS & QR.

What Further Research is Needed

- The expressive power of many qualitative reasoning methods need to be extended in order to allow tackling a wider range of problems
- Ad hoc approaches in use due to the unavailability of mathematically sound approaches should be identified, and progress made in others areas should be incorporated into the field
- Mathematical methods allowing mixing qualitative and quantitative approaches within the same axiomatic framework should be developed

One consequence of this would be that in actual modelling of a problem, no choice has to be made between using either quantitative or qualitative methods.

5.1.3 Integration of Models from Different Domains: Electrical, Mechanical, Hydraulic, etc.

In many situations it is necessary to consider phenomena with different natures in order to reason about a system.

Examples:

- In the field of continuous industrial processes, many devices, such as pumps, comprise phenomena related to hydraulics and mechanics
- In the automotive industry cars comprises different inter-related subsystems such as hydraulic, electric and electronic

Integration of models is an open problem, and further research on this topic is closely related with research on ontologies. Some work has been done using domain independent ways of modelling such as bond graphs, although that work has not been as successful as might have been expected. One of the reasons may be that bond graphs are well suited to simulation, but less adapted for the other tasks performed by model-based systems.

It may be that a combination of appropriate methodologies for individual domains, plus the development of standards in an integrated manner for interfacing models in different domains may finesse this problem, but at present it is still an open problem.

5.2 Important Technologies

These technologies, while important, tend to be needed for a few fields of application, rather than vital to the whole usage of QR. If you are working in that particular field, then the kind of advances discussed here may be vital to you, but they are less important than the first category to the widespread application of MBS&QR.

- models of software
- models to represent system specifications and requirements
- hybrid modelling
- multi-level modelling
- combining qualitative and functional models
- automated model generation from simulation models
- derivation of qualitative models from requirements
- automated modelling
- model-based system identification
- conversion of qualitative models

5.2.1 Models of Software

The modelling of the action and influence of software is an issue for almost any advanced man-made device or system. For example, in the automotive domain, electronic control units (ECUs) containing many thousand of lines of software control the state of vehicle subsystems, and often perform monitoring, diagnosis and reconfiguration of systems. It is necessary to incorporate the actions performed by software in models, in order to understand the state of the device, and perform device-specific tasks. Similar issues occur in other domains, such as model-based reasoning about process control systems.

The deployed start of the art in this area can be represented by the AutoSteve system. Abstract representations of the software as state charts are incorporated within ECU components to reason about the overall behaviour of electrical / electronic systems. State changes within the software are mapped onto electrical path changes in the electrical system, and vice versa. This is adequate for many simple representations of software, but fails to capture the complexity of the software, and so can mean that incorrect results are generated where the software does not exactly mirror the behaviour of the state chart description.

It should be noted that present commonly used software engineering modelling methods such as UML (Universal Modelling Language) do not provide a solution to this problem, as UML is not directly executable - it suffers from the same problem of not necessarily matching the actual computer program implemented.

There are three possible ways in which this situation can be ameliorated. The first is to have an executable description language from which programs can be automatically generated. The model-based system could then interpret the requirements, and use them in reasoning. This might be referred to as automatic programming from requirements, and has been pursued for the last 20 years without notable penetration of the software engineering industry. A second solution is to be able to abstract models from programs and use those models within a model-based system. The third solution is ‘software in the loop’ where the model-based system interacts directly with the chip containing the software, and so the behaviour of the overall system can be modelled with the software that will run in the real system.

5.2.2 Models to Represent System Specifications and Requirements

One of the major advantages of model-based reasoning for problem-solving is that it can consider many more possible scenarios than a human could. One of the key concepts for qualitative model-based systems is that of an ‘envisionment’. An envisionment is a map of all of the possible states that a given system can reach, and how the system moves from one state to another. It is generated by exhaustive simulation from all states to see what other states can be reached.

For systems where safe operation is an issue, an envisionment provides important indications of the possibility of reaching unsafe states or situations. In other types of application, it might be possible to specify “interesting” states of a different sort.

In order to identify interesting / unsafe states, two things are needed:

- Descriptions of what is interesting. This can involve capturing descriptions of the way in which the system should work, and might include issues of complex dynamic time varying and continuous systems, dealt with elsewhere in this section

- Abstraction of state descriptions. It must be possible to abstract the results of an envisionment so that they can be compared with the descriptions of interesting states

This area is in its infancy, but we would expect it to make a significant contribution to system safety and reliability as it becomes better developed.

5.2.3 Hybrid Modelling

Different modelling techniques allow the capture of different aspects of the same phenomenon. Hence, in order to include in one model different aspects of the same phenomenon or even different phenomena, you need to integrate models from different sources.

Examples:
- Pure qualitative models allow one to focus on significant behaviours, while pure numerical models allow one to detail each one of these behaviours or even to solve ambiguities related to the qualitative reasoning
- Causal models and models based on quantitative differential equations provide two different views of the same phenomenon

Few systems are capable of combining different modelling approaches. Currently, the main research effort is devoted to produce and to use semi-qualitative models.

A basic research issue in the QR community for the next decade is the mathematical aspects of the different kinds of models and their inter-relationships.

In the future, model-based systems need to be able to combine different types of models to solve a given problem. The target to be achieved might be the kind of reasoning displayed by human experts, who seem able to combine information from different types of models seamlessly, and to combine information from partial models of each type.

5.2.4 Multi-level Modelling

It is necessary to combine models at different levels of abstraction to solve a particular problem, usually to cope with complexity.

Examples:

- In the food industry, the evaporation station can be modelled at three different levels at least: simple mass balances (product conservation), detailed balances (mass and energy conservation) and detailed dynamical model for control purposes
- In the computer industry, a computer can be seen at different levels, from high-level functional components to chips

Currently, there are different theoretical proposals: automated handling of diagnosis hypotheses, multiple models considering available time for diagnosis, multiple levels of abstraction regarding the quality of the diagnosis. However, there is almost no application on industrial systems capable of handling models at different levels of abstraction, because there is no systematic way to share results from different models within the same task.

A real applicable methodology needs to be proposed to change smoothly from one level to another, exploiting results from different levels.

Eventually the reasoning system should be able to select the adequate level of abstraction automatically, and to switch from one to another as required.

5.2.5 Combining Qualitative and Functional Models

Much qualitative research has concentrated solely on reasoning about the structure and behaviour of systems. For many applications, it is necessary to abstract the results in terms of the function or teleology of the system. That implies being able to represent teleological knowledge, to reason about it, and to map behavioural knowledge to it. This has been done for systems with fairly static behaviour. That work needs to be extended to cover complex, dynamic time varying functions.

5.2.6 Automated Model Generation from Simulation Models

The exploitation of model-based systems in industry will greatly depend on the (additional) modelling efforts they require. This lead us to the attempt of reducing these efforts by automated conversion of existing simulation models into abstract models suited for model-based problem solvers.

Simulation models of a system are often created for control purposes. However, for diagnosis, for example, specific properties are needed from a model:

Needed: A component-oriented model. For achieving the simulation of the system behaviour, the component structure of the respective device is fairly irrelevant. As a result, the subsystem structure of the model does not necessarily reflect the component structure of the device. For instance, a certain pipe might not occur at all in this model. But if diagnosis has to consider the possibility of a leakage or clogging, the component has to represented and modelled.

Needed: Preservation of the physical structure. A typical example of a violation of this requirement is that input and output flow of an aggregate device might be identified by an equation which, again, is based on the assumption of normal behaviour (no leakage occurring).

Needed: Models of faulty behaviour. They are required if we are not only interested in fault detection, but fault (class) identification (as in on-board diagnostics), diagnosability analysis, and FMEA. As long as 'control' is considered as 'controlling the device under normal conditions', faults are not considered in the development of the control algorithms. As a result, they are not part of the respective simulation model. Extending this to include fault models is not always trivial. If faults correspond to deviating parameters, it is fairly straightforward, but in the general case, faults may change the structure of the model radically. For instance, introducing a pipe with the potential to have a leakage means introducing another state variable and affecting the possibility to simulate the model.

Needed: A physically correct simulation model. Since the diagnosis approach is based on identifying discrepancies between a certain behaviour mode (OK mode or some fault) and the respective model, it is crucial that the real physical behaviour is actually covered by (the envelope of) the model. If this is not the case, e.g. because the error functions ε-, ε+ are difficult to estimate, diagnosis runs the risk of detecting model faults rather than component faults and, hence, of generating wrong diagnoses. While we may assume that the normal behaviour is properly covered if the model satisfies the needs of control, it also has to correctly model the behaviour if a fault occurs. In many cases, the models of components are based on an implicit assumption about overall normal behaviour. This may be addressed by an appropriate modelling methodology. However, there is a serious limitation: in particular for complex components, we may lack first principles models, and the simulation model contains characteristic maps that contain empirical data. In this case, the conditions under which these data were obtained (typically normal conditions) are compiled into the model in a way that is hard or impossible to detect.

We should note that only a few of these difficulties really stem from an inappropriate modelling process or modelling faults. Rather, it is the purpose of the simulation models, namely simulating correct behaviour for control purposes, that is in conflict with the diagnostic requirements. Without integrating the views and the work processes concerning system development for control and diagnosis, this will be difficult to change.

There is a need for methodologies that ensure that the models are built correctly in the first place for use in other tasks that simulation, and techniques that make the process of converting those models to ones appropriate for diagnosis and other tasks is a painless process.

5.2.7 Derivation of Qualitative Models from Requirements

During the design process, the correct operation of a system is often described at a high level, perhaps in terms of state charts. Such information is often very useful when performing model-based reasoning. Better methods are needed of integrating it into the construction of model-based systems.

5.2.8 Automated Modelling

Automated model building and model transformation needs continued theoretical work and more effective and efficient algorithms [Ironi and Tentoni, 2003b]. This is emphasized by application requirements. Much of the expected gain depends on fast and economic creation of models from a library. Since different tasks may require models at different levels of abstraction, there is a tension between the desired compositionality and generality (and, hence reusability) of models and the necessity of task-oriented models. QR needs to develop techniques to generate task-oriented models from generic ones.

This also touches upon a more general goal, namely integrating QR results and techniques with standard engineering practice and tools. The lack of integration presents a major obstacle to transferring QR technologies into industrial practice. Deriving qualitative models from numerical ones that have been developed, for instance, in the phase of design verification, is of high practical importance. However, it may require changes in current modelling practice towards modular, component-oriented models. The need to blend in with current practice also applies to other domains, such as medicine, economy, biology and ecology.

5.2.9 Model-based System Identification

Model building is a difficult and time consuming process. A much more efficient alternative to building models by hand would be to learn models from observed data. This is still a very difficult machine learning challenge for complex domains. Qualitative reasoning can help with this in two ways.

Learning qualitative models. In domains such as some areas of biology, where the underlying models may not be known, it will be possible to learn qualitative models from data. Early research in this area indicates that it is more useful to build qualitative models rather than numerical models at this stage, in order to facilitate understanding by domain experts.

Deriving quantitative models from qualitative models. In domains where qualitative models are known, but are not executable, qualitative reasoning provides graphical ways of building executable models, and makes clear the assumptions behind the models, enabling domain experts to compare their models on a like-for-like basis. Where models are known and data is available, it should make it possible to develop accurate numerical models with known assumptions and limitations [Bellazzi and Guglielmann, 2000].

The main impact of these techniques may well be in science rather than in engineering, providing tools for scientists to understand the world better, and having a dramatic impact on the way that we carry out scientific research.

5.2.10 Conversion of Qualitative Models

One issue concerns the development of better engineered and easy-to-use *tools* that facilitate the exchange of results among researchers and make QR techniques available to potential users in other areas and application work. The field, so far, has developed a variety of theories, formalisms, and techniques with different degrees of generality and is still far from delivering a small set of uniform principles and systems. If the field can make progress on this, it will become easier to create and exchange *libraries* of reusable models.

5.2.11 Hybrid Reasoning Systems (Integration of Different Reasoning Technologies)

Different aspects of a given task can be solved more efficiently using different reasoning techniques, such as model-based reasoning, case-based reasoning or knowledge-based reasoning. This fact is even clearer when the reasoning system has more than one task at hand, for instance diagnosis together with monitoring and/or re-configuration.

Examples:

- Diagnosis in industrial processes can be done knowledge-based, model-based or combining results from both
- Reasoning about socio-economic systems usually requires the combination of quantitative, qualitative and experience-based models

A few systems had used hybrid solutions in the past to solve a specific task. Nevertheless, currently there is an increasing interest in this subject in different research communities, not just in MBR. Nowadays research is being done in combining model-based reasoning with heuristic classification systems, heuristic classification and machine learning, and model-based and machine learning among others. Unfortunately, there is no general proposal yet, but a collection of *ad hoc* technological solutions.

Additional research needs to be carried out to bring a formal framework for sharing knowledge among different reasoning technologies. For instance, results provided by a neural classifier should be smoothly interpreted to select an appropriate level of abstraction in a model-based reasoning system. In the long term, these issues could be answered by means of a General Knowledge Theory. Nonetheless, this seems to be a basic research issue for years to come. Hence, current and future research should provide different technological proposals which should be tested in different contexts.

Finally, reasoning systems should be capable of automatically deciding the best technique to solve a given problem.

6 Conclusions

Model-based and qualitative reasoning has shown itself to be a productive technology for practical applications. In the future, both the challenges for the technology and the promise it holds are greater than ever. The visions in this roadmap are intended as encouragements to researchers in the field. We are engaged in an enterprise with immense potential benefits. In order to succeed, we need both people who will drive work on the difficult applications described here, addressing problems of integration with other technologies and commercial issues, and researchers who will solve more of the basic issues that need to be resolved in order to build these visionary systems.

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7.1 Useful Web links

Model-based Autonomous Systems Research Area:
http://ic-www.arc.nasa.gov/ic/projects/mba/index.hml

Livingstone 2 homepage:
http://ic-www.arc.nasa.gov/projects/mba/projects/L2/doc/index.html

DS-1 mission logs: http://nmp.jpl.nasa.gov/ds1/archives.html

X-37 experiments: http://ic-www.arc.nasa.gov/ic/projects/x37ivhm/index.html

Koala homepage: http://juban.free.fr/projects/koaweb/koala.html

8 Document History

Version	*Date*	*Changes made to document*	*Changed by*
1.0	16th December 2005	Original Document Drawn Up	CJP
1.1	24th January 2005	Amendments	RIR
2.0	15th February 2005	Updated with comments from SC, final proof read and status set to Release	RIR