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Chapter 4

Diagnostic Expert Systems: From Expert's Knowledge to Real-Time Systems

C. Angeli [1]

Abstract

This Chapter presents the evolution of the expert systems paradigm for fault diagnosis in technical systems and processes. Fault diagnosis is becoming one of the largest domains where expert systems are find application from their early stages. The process of diagnosing faulty conditions varies widely across to different approaches to systems diagnosis. The application of decision-making knowledge based methods to fault detection allows an in-depth diagnosis by simulating the human reasoning activity. Most of the past applications have been rule based while the automation of the diagnostic process including real-time data and/or modelling techniques added a new dimension to diagnostic task by detecting and predicting faults on line. Combination of expert systems technology with other artificial intelligent methods or with specific classical numerical methods adds more effectiveness to the diagnostic task. These knowledge based diagnostic techniques are presented in this Chapter, technical details of their implementation are provided, the advantages and drawbacks of every technique are outlined, examples from recent research work of expert diagnostic practice in industry are presented and current research trends are underlined to help the reader to delve into the matter.

INTRODUCTION

Fault diagnosis in technical systems has received a lot of theoretical and practical attention over the last years. Diagnosis is a complex reasoning activity, which is currently one of the domains where Artificial Intelligence techniques have been successfully applied as these techniques use association rules, reasoning and decision making processes as would the human brain in solving diagnostic problems.

[1] Department of Mathematics and Computer Science, Technological Education Institute of Piraeus, Konstantinoupoleos 38, N. Smirni, GR-171 21 Athens, Greece

A variety of fault detection and diagnosis techniques have been developed for the diagnostic problem solving process. These techniques include model based approaches, knowledge based approaches, qualitative simulation based approaches, neural network based approaches and classical multivariate statistical techniques.

Expert systems found broad application in fault diagnosis from their early stages because an expert system simulates human reasoning about a problem domain, performs reasoning over representations of human knowledge and solves problems using heuristic knowledge rather than precisely formulated relationships, in forms that reflect more accurately the nature of most human knowledge.

Strategies and capabilities for diagnostic expert systems have been evolving rapidly. Fault diagnosis for technical systems and processes need experiential knowledge in parallel to scientific knowledge for the effective solution of the diagnostic problem solving process. Different diagnostic approaches require different kinds of knowledge about the process. These approaches include first principal knowledge governing the process operation, empirical knowledge such as operators' experiences and historical data about the process operation under various normal and faulty conditions. From the early stage, when Feigenbaum (1981) published the reference for the early expert systems, numerous systems have been built in a variety of domains. Early diagnostic expert systems were rule-based and used empirical reasoning whereas new model-based expert systems use functional reasoning.

Automated diagnostic applications require diagnostic conclusions on-line under time constrains. These expert systems should be able to interpret signals as well as to deliver the required control action, conduct tests and recommend diagnostic procedures. For this purpose these systems should use a combination of quantitative and qualitative methods for fault detection that allows interaction and evaluation of all available information sources and knowledge about the technical process.

In this Chapter these strategies will be examined, the nature of automatic expert diagnostic and supervision systems will be revealed and recent trends in expert systems development will be described. In addition, a reference to the evolution of knowledge acquisition, knowledge representation techniques as well as user interface functions for expert systems will be provided. Examples from recent expert diagnostic practice in industry will be presented as well.

EVOLUTION OF EXPERT SYSTEMS TECHNOLOGY FOR FAULT DETECTION

In the late 1960's to early 1970's, expert systems began to emerge as a branch of Artificial Intelligence. The intellectual roots of expert systems can be found in the ambitions of Artificial Intelligence to develop "thinking computers". Domain specific knowledge was used as a basis for the development of the first intelligent systems in various domain. Feigenbaum (1981) published the best single reference for all the early systems. In the 1980's, expert systems emerged from the laboratories and developed commercial applications due to the powerful new software for expert systems development as well as the new possibilities of hardware.

Feigenbaum (1982) defined an expert system as "an intelligent computer program that uses knowledge and inference procedures to solve problems that are difficult enough to require significant human expertise for their solution". Differences from conventional programs include facts such as: An expert system simulates human reasoning about a problem domain as the main focus is the expert's problem solving abilities and how to perform relevant tasks, as the expert does. An expert system performs reasoning over representations of human knowledge in addition to doing numerical calculations or data retrieval using the knowledge base and the inference engine separately. An expert system solves problems using heuristic knowledge rather than precisely formulated relationships in forms that reflect more accurately the nature of most human knowledge dealing with symbolic values and procedures.

The first diagnostic expert systems for technical fault diagnosis were developed in the early 1970's at MIT as is reported by Scherer and White (1989). Since then numerous systems have been built. Surveys of the first diagnostic expert systems of technological processes are provided by Pau (1986), Tzafestas (1989), Scherer and White (1989). During the period 1985-1995 expert systems were the "hot topics" in artificial intelligence developments due to the attention in knowledge management issue. After 1995 expert system applications started to decline as stand-alone systems and their technology embedded in mainstream of information technology. New expert systems started to combine symbolic with numerical information or with other artificial intelligence techniques to produce more effective systems.

From the early systems gradually emerged a dominant architecture based on separation of domain knowledge and general reasoning knowledge knowing as inference engine. Inference engine was relied on search techniques backward and forward changing. First generation of expert systems was rule-based while later on the model-base approach was emerged,

Rule-Based Diagnostic Expert Systems

Rule-based expert systems have a wide range of applications for diagnostic tasks where expertise and experience are available but deep understanding of the physical properties of the system is either unavailable or too costly to obtain.

In the rule-based systems, knowledge is represented in the form of production rules. A rule describes the action that should be taken if a symptom is observed. The empirical association between premises and conclusions in the knowledge base is their main characteristic. These associations describe cause-effect relationships to determine logical event chains that were used to represent the propagation of complex phenomena. The general architecture of these systems includes domain independent components such as the rule representation, the inference engine and the explanation system. Basic structure of a classical rule-based expert system is presented in Figure1.

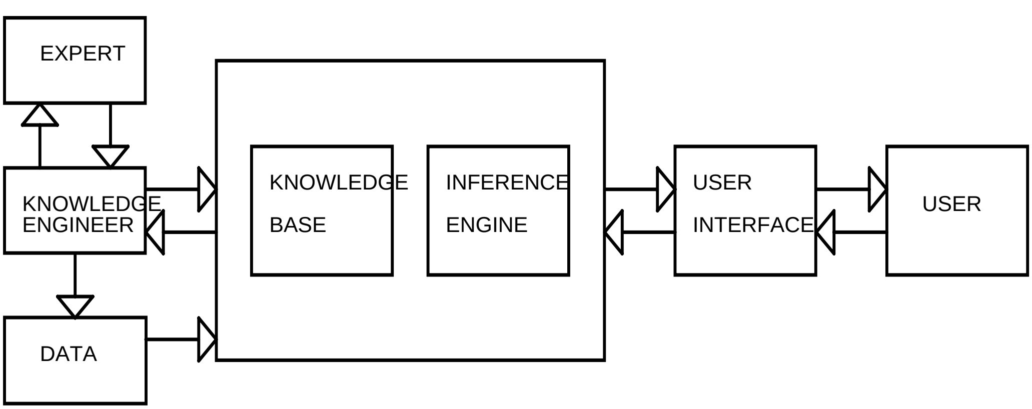

Figure 1: Basic structure of a rule-based expert system

Experiential knowledge suitably formatted consists the basis for the classical expert system approach. Fault diagnosis requires domain specific knowledge formatted in a suitable knowledge representation scheme and an appropriate interface for the human-computer dialogue. In this system the possible symptoms of faults are presented to the user in a screen where the user can click the specific symptom in order to start a searching process for the cause of the fault. Additional information about checking or measurements is used as input that, in combination with stored knowledge in the knowledge base guide to a conclusion.

Widman et al (1989) have counted the limitations of the early diagnostic expert systems as follows:

1. Inability to represent accurately time-varying and spatially varying phenomena.
2. Inability of the program to detect specific gaps in the knowledge base.
3. Difficulty for knowledge engineers to acquire knowledge from experts reliably.
4. Difficulty for knowledge engineers to ensure consistency in the knowledge base.
5. Inability of the program to learn from its errors.

The rule-based approach has a number of weaknesses such as lack of generality and poor handling of novel situations but it also offers efficiency and effectiveness for quasi-static systems operating within a fixed set of rules. In the modelling of human problem solving process it can guide users in a step by step manner to achieve a conclusion.

A decision tree is the main technique that defines the various logical paths that knowledge base must follow to reach conclusions. From the decision tree the relevant rules to each node can be written and so the initial knowledge base can be constructed.

Problems that are easily represented in the form of a decision tree are usually good candidates for a rule based approach. In the following example a rule is presented as it is needed to make a decision:

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if      ?'reduced pressure' is Yes and
        ?'down' is No and
        ?'motor' is No
then    ?'electrical failure' is Yes.
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In this rule the system searches for the topics 'reduced pressure', 'down' and 'motor' to satisfy the rule. Each of these rules may be further a set of rules, or simply a question asked to the user.

Rule based systems do not require a process model; however they do require a multitude of rules to cover all possible faults in a technical system and have difficulties with unexpected operations or new equipment. Among the main limitations of the early diagnostic expert systems are considered the inability to represent accurately time-varying and spatially varying phenomena, the inability of the program to learn from errors as well as the difficulties for knowledge engineers to acquire knowledge from experts reliably.

Most of the early expert systems were mainly laboratory prototypes that only briefly made into full operation in an industrial environment.

Model-based diagnostic expert systems

In model-based fault detection a model (mathematical or heuristic) is employed to describe the nominal behaviour of the monitored system. The generated residual signals that indicate differences between the model's output and measured process output are interpreted and evaluated to isolate faults.

Fault detection is realised after checking some measurable variables of a system in regard to a certain tolerance of the normal values and taking an appropriate action when a limit value is exceeded. Residuals are generated by comparing the sensed measurements to the predicted output of a model. The residuals are expected to be close to zero in fault free cases, but are distinguishably different from zero in the case of a fault in the system.

Model-based reasoning is a broad category that describes the use of variety of engineering models and techniques for fault diagnosis.

Model-based diagnostic expert systems have eliminated some limitations of the early expert systems. In these systems expert knowledge is contained primarily in a model of the expert domain. Model-based diagnosis uses knowledge about structure, function and behaviour and provides device-independent diagnostic procedures. The use of models enables the estimation of variables and parameters which are influenced by the fault. In addition model-based methods have the potential of early detection of slowly developing faults in complex processes.

Model-based diagnostic expert systems offer more robustness in diagnosis because they can deal with unexpected cases that are not covered by heuristic rules. In addition these systems are able to detect incipient faults in a technical process. The development of knowledge bases of such systems is less expensive because they do not require field experience for their building and are more flexible in the case of design changes. Model-based diagnostic systems offer flexibility and accuracy but they are also domain dependent. Real time implementation of model-based expert systems use enormous amount of computational capacity. The construction and updating of their knowledge bases are very demanding.

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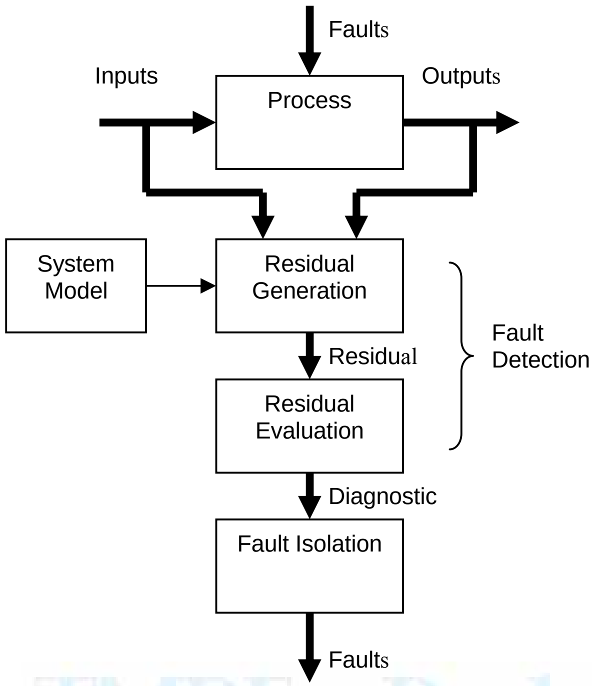

Figure 2: Fault diagnosis using system models

Difficulties with model based fault detection methods arise from the fact that the accuracy of the measurements needed to calculate the evolution of faults should be of high quality. In practice, fault detection systems make usually use of measurements from process instrumentation that is not necessarily installed for this purpose. In consequence, the instrumentation may not be sensitive enough and special sensors should be connected to the process equipment. Use of model-based methods may require assumptions about the process that are not valid, such as the assumption that the process is linear as well as that the influence of noise and disturbances to the fault detection process is of minor importance.

Recent contributions to model based fault diagnosis include Basseville and Nikiforov (1993), Patton et al (1995), Gertler (1998),Chen and Patton (1999), Soliman et al. (1998), Frank et al (2000), Cordier et al (2000), Leung and Romagnoli (2000), Mangoubi and Edelmayer (2000), Zhang et al (2002), Angeli and Chatzinikolaou (2002), De Kleer and Kurien (2003), Heim et al (2003), Korbicz et al (2004), Isermann (2005), Yusong et al (2006), Fekih et al (2006).

On-line diagnostic expert systems

On-line diagnostic expert systems usually use a combination of quantitative and qualitative methods for fault detection that allows interaction and evaluation of all available information sources and knowledge about the technical process. In these systems although basic diagnostic procedures are very satisfactory, real-time issue such as sensors drift can lead to problems with nuisance alarms in a system.

On-line use has also revealed the need for long and dead-time considerations along with simple high/low limit and rate detection.

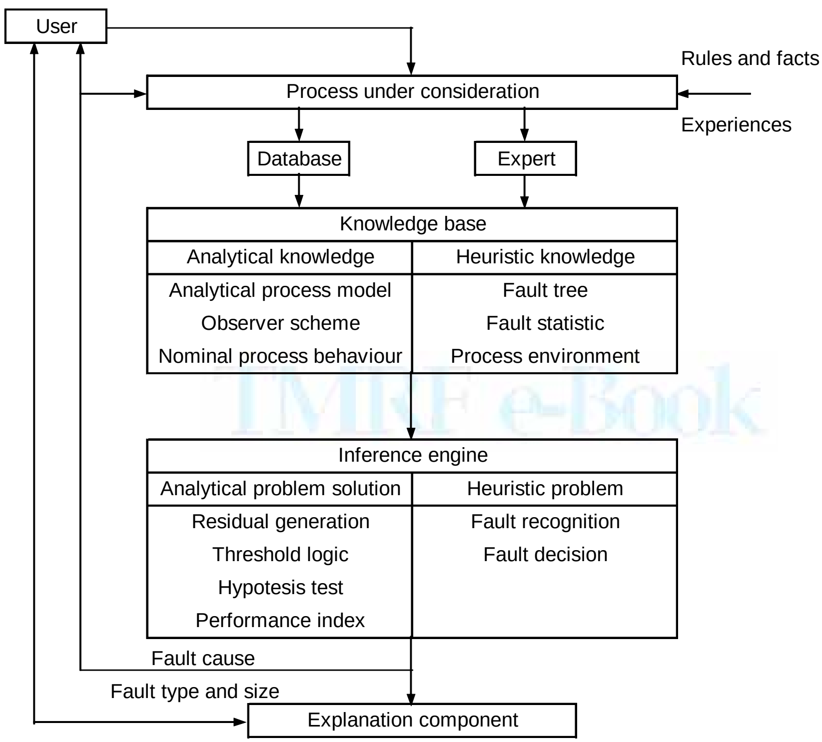

Figure 3: Basic structure of an on-line expert system (after Frank 1990)

The basic structure of an on-line expert system is presented in Figure 3. One of the main characteristics of this system is that in parallel to the knowledge base of the traditional expert system a data base exists with information about the present state of the process that interacts with the knowledge base of the system. The information of the data base is derived on-line from the sensors. This database is in a state of continuous change. The knowledge base of the system contains both analytical knowledge and heuristic knowledge about the process. The knowledge engineering task comprises different knowledge sources and structures. The inference engine combines heuristic reasoning with algorithmic operation in order to reach a specific conclusion. Response time is a critical issue for on-line expert systems because they are operating in parallel with a dynamic process.

Calculations and fault detection must be performed in a specific time in order to perform fault diagnosis and control in a suitable time. In addition, the quality of the incoming data from the external environment plays a primary role in the diagnostic process. Poor quality of data due to the time variation or sensor performance may be result inappropriate diagnostic conclusions.

When models of the technical systems are incorporated to the fault detection system using traditional, theoretical modelling techniques that are usually used for the detailed modelling of faults are not suitable for on-line performance of a system because these techniques need time for the running of the models of faults and in on-line systems it is required to reduce this time to the shortest possible. In addition, knowledge base development techniques of are not the required for on-line performance since updating from the sensor measurements and possibilities for the interaction of different sources of knowledge is needed.

In Table 1 the main advantages and disadvantages of each expert systems technology regarding the diagnostic processes for technical systems are summarized.

ADVANTAGES	DISADVANTAGES
Knowledge-based methods for fault detection	
a. Rule based diagnostic expert systems	
Rules can be added or removed easily	Lack of generality
Explanation of the reasoning process	Poor handling of novel situations
Induction and Deduction process is easy	Inability to represent time-varying and spatially varying phenomena
A process model is not required	Inability to learn from their errors
Efficiency and effectiveness in fault detection	Difficulties in acquiring knowledge from experts reliably
	Development and maintenance is costly
b. Model based diagnostic expert systems	
Device independent diagnosis	Domain dependant
Knowledge acquisition is not needed	Difficulties in isolation of faults
Ability of diagnosing incipient faults	Knowledge bases very demanding
Deal with unexpected cases	
Flexibility in the cases of design changes	
Dynamic fault detection	
c. On-line diagnostic expert systems	
Real time fault diagnosis	Domain dependant
Ability to handle noise	Good models are required
Generalization	Require considerable data
Fast computation	Inability to explain the reasoning process
Ability to handle with dynamics	Computationally expensive

Table 1: Expert system techniques for fault detection and diagnosis

The development environment

Historically the first expert systems were developed using the Lisp programming language as suitable for the manipulation of symbolic information. During 1980's Prolog gained some popularity. In the cased that speed and interaction with various kind of information was required their implementation language were considered. In 1990's logic programming languages were used for expert system applications. Expert system shells have been also used especially in 1980's providing a wide range of facilities for developers. In 1990's commercial products were extended with object oriented characteristics or real-time implementation features. Recently researchers have proposed interactive environments according to the needs of specific applications.

The development environment for expert systems applications in engineering systems should be suitable for interaction of several functional areas. On-line expert systems in engineering applications require, in addition to symbolic representations, high precision solutions that can be mathematically formulated.

The appropriate development environment should support capabilities of effectively coupling symbolic and numerical techniques. On the other hand expert system tools are not well-suited to dealing with numerical processing due to their focus on symbolic representations.

Recent research work of on-line expert systems

On-line knowledge driven techniques have been developed the last few years. A survey paper on the early attempts of applying on-line knowledge-based systems to solve problems in domains such as aerospace, communications, finance, medicine, process control and robotic systems is published by Laffey et al (1988).

The authors emphasise that the surveyed applications have not progressed beyond the prototype state. The main reason for this situation was the lack of suitable tools specifically built for real-time monitoring as well as the limitations of inference engines in high-performance to guarantee response times.

In following, recent published research work in diagnostic on-line expert systems for technical processes is presented in detail. These systems are selected after an extensive research through the literature. The presentation of these systems includes some details of their application while a more extensive presentation is out of the scope of this paper.

Angeli and Atherton (2001) developed an on-line expert system to detect faults in electro-hydraulic systems using on line connections with sensors, signal analysis methods, model-based strategies and deep reasoning techniques. Expert knowledge is contained primarily in a model of the expert domain. The final diagnostic conclusions are conducted after interaction among various sources of information.

Saludes et al (2003) reported a fault detection and isolation scheme for hydroelectric power stations based on a neural network and an expert system subsystems. The expert system stores knowledge acquired by operators for the diagnostic conclusions while the neural network has been trained with data automatically collected for one year in order to decide between normal and abnormal states. This system was in the implementation state at the time of the report.

Koscielny and Syfert (2003) presented main problems that appear in diagnostics of large scale processes in chemical, petrochemical, pharmaceutical and power industry and proposed an algorithm for decomposition of a diagnostic system, dynamical creation of fault isolation threads and multiple fault isolation, assuming single fault scenarios.

Yu Quian et al (2003) presented the development and implementation of an expert system for real time fault diagnosis in chemical processes that provides suggestion to the operator when abnormal situations occur. Industrial applications to the fluid catalytic cracking process in refinery are also presented.

Nabeshima et al (2003) reported an on-line expert system for nuclear power plants that uses a combination of neural networks and an expert system in order to monitor and diagnose the system status. The expert system uses the outputs of the neural networks generated from the measured plant signals as well as a priori knowledge base from the pressurized water reactor. The electric power coefficient is simultaneously monitored from the measured reactive and active power signals. Angeli and Chatzinikolaou (2004) have developed an on-line intelligent process monitoring and diagnosis system where acquired data from an actual electro-hydraulic system are recorded, analysed and presented in a suitable format to obtain the information needed for the control and detection of possible faults in proportional valves. The diagnostic system uses cooperatively information and knowledge for the final real-time diagnostic conclusions.

Carrasco et al (2004) reported an on line diagnostic system for the determination of acidification states on an anaerobic wastewater treatment plant that uses expert knowledge to determine the acidification state of the process and on-line measurements of system variables classified in linguistic information using fuzzy-based rules. The reasoning process is realised by evaluating the inference system for the given inputs.

Yusong Pung et al (2006) have described the architecture of an expert system for fault diagnosis in a hydraulic brake system where the acquired knowledge for the knowledge base is based on software simulation. This simulation-based knowledge generation in combination with fuzzy knowledge representation is used for the final diagnostic reasoning.

Current trends in diagnostic systems development

Several researchers combine numerical with qualitative methods the last few years and various methodologies have been proposed for the combination of knowledge-based techniques with numerical techniques considering that the combination of both approaches in an effective way offers an appropriate solution for most situations. In these knowledge-driven techniques, although the governing elements are symbolic, numeric computations still play an important role by providing certain kinds of information for making decisions.

Relevant recent research work is reported by Chen and Patton (1999), Frank et al (2000), Patton et al (2000), Manders and Biswas (2003), Nyberg and Krysander (2003), Saludes et al (2003), Koscielny and Syfert (2003), Persin and Tovornik (2003), Gentil et al (2004), Korbicz et al (2004), Wang (2006).

Current trends include coupling of these diagnostic techniques in order to produce more effective tools as well as combining expert systems technology with other artificial intelligence technologies as neural networks or genetic algorithms to cover various requirements of the diagnostic process. Hybrid intelligent systems can offer powerful tools to complex problems (Patton et al 2000; De Kleer 2003; Nyberg et al 2003; Biswas 2004; Liu et al 2005; Su and Chong 2006; De Boer and Klingenberg 2008).

Recently diagnostic expert systems are find application in network conditions. Web-based expert systems are based on traditional expert systems technology, rule-based and case based reasoning primarily. They incorporate client-server architectures and web browser-based interfaces (Grove 2000; Duan et al 2005). Fault diagnosis in networked condition offer new possibilities for the diagnostic task (Fang et al 2006).

EVOLUTION OF KNOWLEDGE AQUISITION TECHNIQUES

The knowledge acquisition bottleneck has not been solved but over past years research in that area has provided some useful results. In the field of expert systems, the distinction between "deep or model-based or fundamental" systems and "shallow or compiled or empirical" systems has been given considerable attention by researchers over the last years. Limitations of knowledge acquisition process for technical and anthropological reasons result in limitations of acquired empirical knowledge. In addition, the specific problem dependent nature of the empirical knowledge lacks in robustness compared to the deep models. On the other hand, scientific knowledge of the model-based systems cannot cover the total range of diagnostic tasks, since the diagnostic activity is based mainly on experience.

Building an expert system involves the elicitation of the expertise of a human expert and the translation of the knowledge thus attained into a machine-executable form. Knowledge acquisition is classically referred to as the bottleneck in expert system development by Feigenbaum (1981), since the resulting expert system depends on the quality of the underlying representation of expert knowledge. Unfortunately, an adequate theoretical basis for knowledge acquisition that requires a classification of knowledge domains and problem-solving tasks as well as an improved understanding of the relationship between knowledge structures in human and machine has not been established (Foley and Hart 1992).

Experiential knowledge is acquired over a number of years' experience and consists of much more than just facts and rules. If all symptoms for all malfunctions are known in advance then a simple table lookup would be adequate for the fault specification. The usage of the expertise, that involves weighing up different pieces of evidence in order to choose the most appropriate one for the specific situation using sometimes unknown heuristics, helps decidedly in the problem solving process and particularly in making useful or accurate decisions or diagnoses.

Over the last few years, researchers from the field of cognitive science have proposed a variety of techniques for the knowledge acquisition process. These techniques range from the formal to informal, from those which are driven by the knowledge engineer to those which are driven by the expert and from those which are visible to the expert to those which are hidden. Interviews, protocol analysis and repertory grid analysis are characterised as traditional techniques to the knowledge acquisition process. Automatic induction techniques have also been proposed by researchers. Interviews are considered as the most popular and widely used form of expert knowledge acquisition (Hoffmann 1992; Foley and Hart 1992). One serious drawback of interviews is the fact that they are time-consuming. In addition, the effectiveness of interviews depends on the skill of the interviewer in posing suitable questions and the skill of the expert in conveying his knowledge and techniques.

Task performance and protocols hand the task of guiding the “interview" over to the expert by requiring that the expert thinks-aloud while working through a series of either simulated or written case examples. In this method, the study of an expert's action is sometimes called protocol analysis. It has been adopted from the cognitive science and has been automated quite early in artificial intelligence (Waterman and Newell 1971). This method is considered by Holsapple et al (1994) as more efficient for complex cases than for relatively simple cases.

Repertory grid method yields a set of dimensions defining the space which contains the domain objects. The knowledge engineer decides on a list of elements first and then presents them in trees asking the expert to indicate how one of them differs from the other. This technique is useful in clustering information but requires a lot of time to work effectively.

Researchers try to automate the knowledge elicitation process from early stages by proposing knowledge acquisition software methods. Attempts in this direction had produced a great variety of approaches such as Gaines and Boose (1988), Michie (1982) and a great number of implemented systems such as by Boose et al (1987), Quinlan (1986), Clement (1992). Knowledge acquisition software methods include machine induction or induction by example tools and knowledge elicitation tools.

Mettrey (1992) considers induction tools as ineffective for complex applications where knowledge representation and reasoning capabilities are required. Knowledge elicitation tools consist of computer programs that guide the expert to enter information about a domain into a computer and to classify this information in order to generate rules from the organised data. Tools for automatic knowledge acquisition are described by Newquist (1988), Diederich et al (1987), Clement (1992), Badiru (1992).

The next decade, new arrivals such as neural networks (Cooke 1992), genetic algorithms (Odetayo 1995) and hypertext (Pouliezos and Stavrakakis 1994) have also been proposed as automated knowledge acquisition methods.

Cooke (1992), criticising the common knowledge elicitation techniques, considers, firstly, that they have limitations to the extent that they first rely on verbal knowledge which is often inaccurate and incomplete; secondly that they miss much knowledge which is automatic or compiled; thirdly that they produce output that requires extensive interpretation in order to transform it into a computer usable format; and fourthly that they ignore the organisation or the structure of the facts and rules elicited which is a critical point because experts differ to novices not only in the facts and rules they use, but also in the way that the facts and rules are organised in their memories.

Automated methods have also been criticised in that most of the proposed knowledge engineering tools are used to translate the already elicited knowledge into a computer program rather than to perform knowledge elicitation itself.

Much recent research effort in the field of knowledge acquisition (KA) has focused on extending knowledge acquisition techniques and processes to include a wider array of participants and knowledge sources in a variety of knowledge acquisition scenarios as (Xiong et al 2002; Wagner et al 2002; Xing et al 2003; Wagner et al 2003; Wu et al 2003; Gale 2005; Chen et al 2008). As the domain of expert systems applications and research has expanded, techniques have been developed to acquire and incorporate knowledge from groups of experts and from various sources.

One of the advantages of the *model-based* expert systems is the avoidance of the knowledge acquisition process as the knowledge is involved in the embedded model of the domain. But on the other hand, model-based diagnostic systems are criticised as not always being able to pinpoint the faulty component (Koseki 1992), and sometimes a lot of tests are required to reach a conclusive decision due to the lack of heuristic knowledge. Hart A. (1992) has also pointed out that no diagnostic analysis is complete without face-to-face discussion with the expert.

In on-line expert systems the knowledge engineering task is different since the knowledge engineer has to combine different knowledge sources and structures. The technological or scientific knowledge (knowledge of functioning) from the domain model has to be combined with the experiential knowledge (knowledge of utilisation) from the domain expert. The characteristics of knowledge to be acquired depend on the nature of the domain as well as on the level of expertise of the domain expert. Current trends include experiential knowledge to complement the scientific knowledge in order to model more precisely the expert's reasoning activity, and to gain the efficiency of heuristics and the advantages of a real world application.

The empirical knowledge and the scientific knowledge usually solve different parts of the overall problem domain cooperatively. Deep knowledge involves concepts of cause that are not available to the relatively compiled knowledge. Empirical knowledge is particularly useful in the diagnostic phase since the target is to find the specific faulty element and not only to declare a faulty behaviour of the system but to propose specific actions. Scientific knowledge is useful for representing the dynamic behaviour of a system or for predicting future faults. The interaction of the two types of knowledge driven by the current problem solving circumstances gives a power to the interaction process.

Experiential knowledge is acquired by the domain expert for specific problem solving requirements. This knowledge refers to the limits for detecting faults, to the decision about a faulty element in specific cases, to the detection of multiple faults as well as to giving advises on the way the logic signal information should be used effectively so that to avoid additional checks in detecting faults. There is no universal agreement on which knowledge acquisition technique should be used in a specific case. The knowledge engineer should decide on the suitable knowledge acquisition method by weighing up the ease with which they can be used against the quality and amount of information being obtained, according to Hart (1992). The choice of the knowledge acquisition method depends on problem domain factors such as size and complexity. It is common to start with interviews and then apply other methods when considered useful.

Knowledge acquisition phase could conclude using diagrams to clarify that the acquired knowledge was suitable for solving the problem. The data organised in diagrams specify which data item is directly or indirectly related to others and in what order. At the end the expert criticise the diagrams, provide missing information and corrected any errors in this formulation. These diagrams led easily to the final construction of the decision tree in the knowledge representation phase.

EVOLUTION OF KNOWLEDGE REPRESENTATION TECHNIQUES

The available knowledge must be properly represented for the problem solving procedures. In the development of knowledge-based systems, an essential element lies in the organisation of the knowledge and the reasoning strategies. Various knowledge representation techniques are available. Some of them are suitable for the majority of problems. Basic data-structures generally used for symbolic representations are production rules, semantic networks, frames, predicate logic and hybrid architectures. The choice of the most suitable representational schema depends on the type of procedural control required and the degree of familiarity of the knowledge engineer with a technique.

There are, however, problems that require unique knowledge representation techniques. The engineering diagnosis process is typically a mixture of empirical and functional reasoning coupled with hierarchical knowledge. Formalism is needed to hierarchically express the structural behavioural knowledge.

In *rule based expert systems* the rules corresponding to the nodes of the decision tree can be written. In *model-based expert systems* knowledge could represent by the mathematical model of the system. In an *on-line expert systems* the knowledge engineering task requires a knowledge representation model suitable for the integration and combination of the two different knowledge sources and structures that are involved in the problem solving process: the first principal knowledge or scientific knowledge and the empirical knowledge.

Current trends include representation of different nature of knowledge can be of different types of representation model. Their interaction should not require that both types of knowledge are of the same representation, or the problem-solving methods that use this knowledge are the same.

The scientific knowledge could represent by the mathematical model of the system in a numerical formation and the experiential by the knowledge base of the system in a symbolic formation. Scientific on-line knowledge coming from sensor measurements should interacted with both the knowledge of the mathematical model and the knowledge base of the system. The representation and the on-line interaction of all these types of knowledge initially required a suitable environment.

EVOLUTION OF USER INTERFACE TECHNIQUES FOR EXPERT SYSTEMS

The User Interface, the third major component of an expert system which allows bi-directional communication between system and user is considered to be a critical part of the success of an expert system.

It has been argued that user interfaces of expert systems are even more troublesome and vital than those of traditional systems because the expert system must present not only the conclusions of the task but also the explanation of the processes by which the conclusions are reached. Consequently the system does not just assist with task performance, but actually assists with decision making about tasks and task performance (McGraw 1992).

The two main areas in the construction of expert systems that involve interface issues are the type of dialogue control and the explanation facilities. In on-line expert systems the role of the user interface is different because they operate in relation to a continuous process and the response time is a critical issue. In addition, on-line systems operate autonomously so that the role of the dialogue control is quite restricted. According to Buck (1989), these systems do not generally respond to user-initiated interrogations but to the process-initiated situation, and in this respect they differ from traditional advisory systems as well as from controller systems that only transfer information from the system to the controlled process. Thus the user cannot directly control their behaviour.

Even on-line systems that are operating under time constraints must be able to explain the reasoning process at the user’s request or to give advice quickly to the user. The advice can be produced at any time while the system is executing different procedures. The explanation of the reasoning can be produced in a specific time after entering a required piece of information. This is not acceptable when the system is controlling or monitoring a dynamically changing process.

A good interface should serve the user in a comprehensible way that matches the manner that a user conceptualises the task in terms of syntactic requirements and semantic organisation and the performance of the task since, from the user’s point of view, the interface is the system. Intelligent systems offer new opportunities for more flexible dialogue.

A key aspect of developing a useful interface is the notion of conceptual models designed into interfaces by their designers and the actual mental models that are developed in the user's mind as they interact with the systems.

The determination of the user’s views to the domain and to the system has as a consequence the experimentation with ways to transfer this understanding to user interface components by selecting a suitable metaphor. People usually attempt to make sense of something new by comparing it with and generalising from what they know about something similar (metaphorical reasoning). A successful metaphor allows operations that are similar to those in the user's problem domain. The problem is to find metaphors with familiar or easily interpreted objects and actions within a system.

Researchers have proposed various models for human-computer interaction analysis. Card, Moran and Newell (1980) proposed the GOMS (Goals Operators Methods and Selection rules) to support the explicit analysis of user tasks at different levels of description. This framework is intended to evaluate the usability of the interface design.

Norman (1986) postulates that the goal of the user and the system state differ significantly in form and content so that it creates a gulf between them. The problem is related to the difficulties of linking psychological goals to the physical variables and controls of the task. This gulf model includes the terms "gulf of execution" and the "gulf of evaluation" between users' goals and knowledge and the level of description provided by the system. It can be bridged using commands and mechanisms of the system to match the user's goal as much as possible.

Shneiderman’s (1992) syntactic / semantic model highlights that users have syntactic knowledge about device-dependent details and semantic knowledge about the concepts. Semantic knowledge has two components; task domain and computer domain. Within the domains knowledge is divided into actions and objects. This knowledge is concerned with the meaning of objects and deals with relationships between objects and their attributes. Syntactic knowledge is arbitrary and therefore acquired by memorisation.

Many researchers have criticised the models that deal with only one of the gulfs presented by Norman (1986), the gulf of execution (how we convert our intention into action) and don’t deal with the gulf of evaluation (how we interpret the system state) or that models are too complex to be used and to understand on an everyday basis.

Many of the modelling techniques offer the designer a way to analyse a system without directly involving the user. The advantage of this approach is that involving the user is often time consuming.

The disadvantage is that modelling techniques only inform us of the potential difficulties that users might encounter due to the lack of information of the real problems that users experience. It is often pointed out that developments in the area of user models will lead to the provision of better interface functions. Very few expert systems being developed at present entail more than the very simplest of user models as much work in this area is at the research level.

Concepts of the models can provide usefulness in systematising efforts for designing interactive systems or in comparing different possible designs or in telling in advance exactly how a system should be designed from a human point of view. The end users of this system are mainly engineers. They prefer more schematic diagrams to the problem solving strategies they use. A style of interface with graphical explanations, hypertext or windowing is needed.

The explanation facility, one of the key characteristics that sets expert systems apart from traditional software systems, improves the ability of the system to totally mimic the human expert as it can provide explanations for the basis of its conclusions. During the testing of the development process of an expert system, the explanation facility helps developers to test and debug the system. A deep explanation facility enables users to check whether the system is taking important variables and knowledge into account during the reasoning process.

User interfaces for expert systems that adapt to the users are beginning to be developed. This includes adapting screen messages, help facilities and advice to meet the user's needs. The user model is the main source that makes explicit assumption about the user useful for the design of system responses, help or explanations which meet the expected needs of the user.

AN EXPERT SYSTEM MODEL FOR ON-LINE FAULT DIAGNOSIS

In following the reasoning process of a model expert system for on-line fault diagnosis will be presented. The reasoning process for real-time dynamic systems requires on-line interaction of various sources of available information in order to produce a reliable and useful knowledge based diagnostic system. In this example an effective interaction of real-time numerical information obtained by an actual system and symbolic knowledge for diagnostic purposes. The decision making process is performed after co-operation of dynamic modelling information, on-line sensor information, and stored knowledge using suitably formatted DASYLab modules.

This expert system example detects faults in hydraulic systems after suitable interaction of knowledge and information. This process is performed on-line and the system is able to respond to dynamically changing states by combining modelling information, on-line sensor measurements and symbolic data.

The actual system used for the experimentation process of this work was a typical electro-hydraulic system consisting of a hydraulic motor controlled by a proportional 4-way valve with a cyclical routine which requires a high speed for a short period of time and then returns to a low speed.

The actual system was modelled in terms of mathematical equations and the simulation program was written in C programming language. The developed mathematical model takes into account the non-linear character of hydraulic systems and the incompressibility of the hydraulic fluid in the pipes as well as the special characteristics of the hydraulic elements used. The technical specifications and function curves were used in order to obtain parameter values given by the manufacturer, after laboratory testing, and the quasi-steady character of the hydraulic elements is also taken into account in order to reduce the complexity of the equations, so that the model can describe more accurately the actual system.

The DASYLab software was used for data acquisition and control purposes as well as for comparison of measured values and relatively calculated quantities using suitably connected modules. The expert system is developed in two parts. The first part performs the numerical calculations while the second part performs the symbolic representations. A data acquisition, monitoring and control module generates and interprets signal values coming from an actual hydraulic system. Measurable quantities of the variables correspond to the pressure at critical points of the hydraulic system and the angular velocity as well as the digital input signals are transferred to the expert system for the decision making process.

The mathematical model of the actual system that generates additional information for comparison with measured variables is also involved in the fault detection method. The evaluation of deviation limits between the performance of the system and the performance of the fault free model stimulates the fault detection procedure. The diagnosis of faults is performed through the knowledge base of the expert system. This system requires a knowledge base architecture that permits the interaction of sensor information, modelling information and experiential knowledge symbolic representation.

The fault diagnosis process

The measured values of the important system variables are compared with the calculated quantities from the simulation program and their deviation is translated to qualitative information. Measured and calculated values of the important system variables are compared in the first part of the expert system that has been developed using the capabilities of the DASYLab software. In following the on-line comparison process between measured and simulated values of the pressures p_a, p_b and the angular velocity ω is presented as well as the transformation of the comparison results to linguistic variables. These linguistic values are used for the fault detection process and the final diagnostic conclusions by the knowledge base of the expert system. The comparison process of measured and calculated values of pressure at different point and the angular velocity are presented in Figure 4.

Figure 4 represents a part of the DASYLab "worksheet" developed for that purpose. The module "outmo3:" corresponds to a file "outmo3.asc" that contains the numerical data from the simulation process. These values are read in order to be compared with the measured values. The "Action00:" module is used to initiate various actions. The "outpr3:" module is used to read the measured values of the pressures p_a, p_b from the file "outpr3" that is produced by the data acquisition system.

The processing of the pressure p_a is performed by the following modules: The "Y/t Chart00:chart" module displays the measured values of the pressure $p_{a.}$ The " Pam-Pas:" module calculates the differences between the pressure and the measured values of the pressure p_a. The "abs(DPa):" module calculates the absolute values of the difference of pressure p_a , Pam-Pas. The " Statistics03:" module calculates the mean value of the differences between Pam-Pas. The " Pa:" module sends the message "OK" in the case that the difference between Pam and Pas is 0 to3 bar, "SMALL" in the case that this difference is 3 to 6 bar and "MED" in the case of difference 6-10 bar to the message module "DPo OK?". This information is used by the expert system to determine more precisely a faulty element. This "DPa OK?:" is a message module that writes the values "OK", "SMALL" and "MED" to the text file "fpa.txt". Similar processing has been performed for the pressure at other points of the hydraulic system.

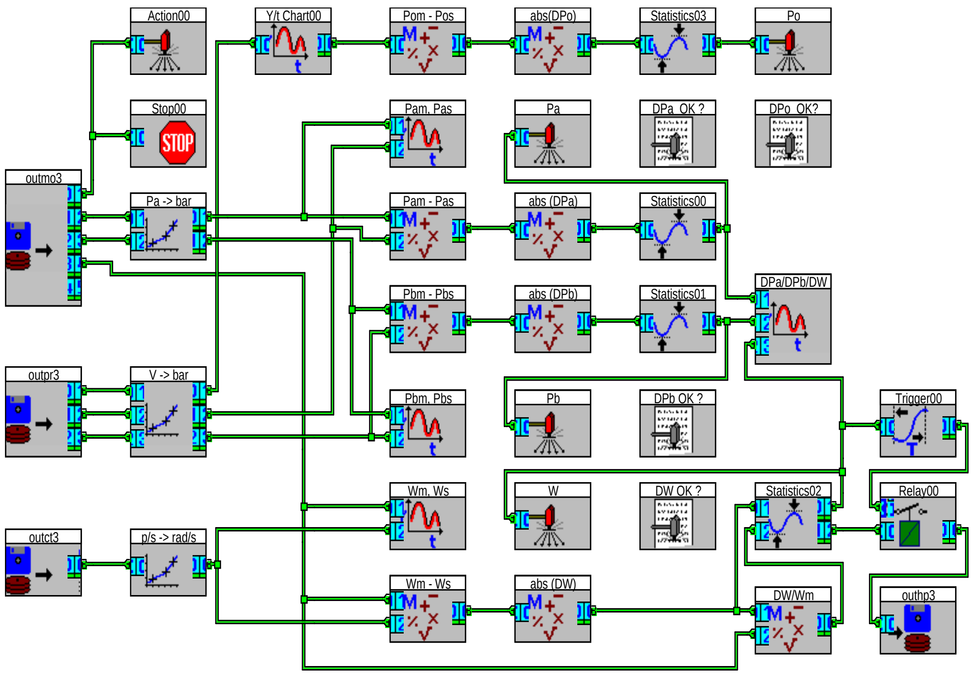

Figure 4: Comparison of measured and calculated data

Output of this worksheet are the files "fpa.txt", "fpb.txt" etc. that include text information about the presence of a fault in p_a, p_b, respectively. These files are used by the expert system as input together with the text file information coming from the data acquisition process.

This symbolic information can be passed in the structure of the knowledge representation scheme and can trigger specific set of rules that are organised under the structure of the topic.

The knowledge base development

The interaction of the various sources of information and knowledge was realised by knowledge representation scheme the "topic". This programming structure offers the opportunity to read external linguistic information from files that can be combined with the stored knowledge. Rules are embedded in topics so that the structure of the final application is a collection of topics. Rules that refer to general assumptions and are represented to specific branches of the decision tree are grouped and embedded in a specific topic. In the structure of a "topic" interact stored knowledge in rules and external information from files coming directly from the data acquisition system pre-processed and transformed to linguistic values.

The interaction of all available information sources in the structure of a "topic" is schematily presented in Figure 5. The symbolic representation of the empirical knowledge and the part of scientific knowledge embedded on the circuit diagrams is realised using the second part of the expert system while the first part is used for the representation of the scientific knowledge coming on-line from sensors, the results of the performance of the mathematical model and the comparison of the results of both interactions. These comparison results continuously update the knowledge base of the expert system.

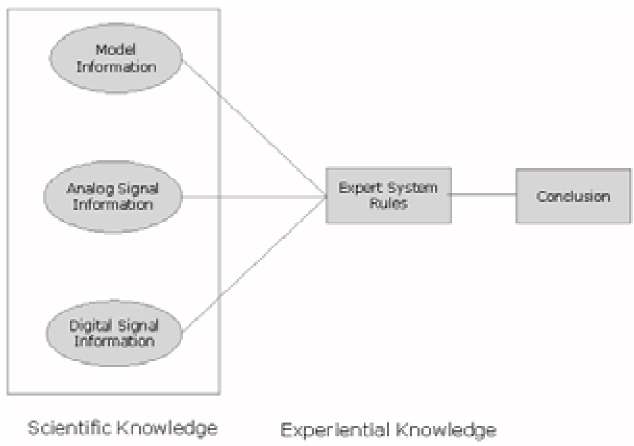

Figure 5: The knowledge base system architecture

SUMMARY AND CONCLUSION

Diagnostic problems are considered as ill-structured problems where there are no efficient algorithmic solutions because all the symptoms for all faults are not known in advance. The effectiveness of diagnostic reasoning lies in the ability to infer using a variety of information and knowledge sources, connecting or selecting between different structures to reach the appropriate conclusions.

Expert systems technology has been widely adopted by many software development companies and industry. Although originally expert system were seen as stand- alone systems now are components of large information technology architectures. As applications become more complex for the requirements of increasing automation, the suitable technique to perform diagnostic reasoning can be quite challenging. The challenge of the future is the development of generic diagnostic architectures that can potentially use a variety of diagnostic techniques, process independent and modular in design so that they can be applied to all the essential equipment.

In this paper, the evolution of expert systems paradigm for the solutions of the diagnostic problem have been presented as well as the evolution of knowledge acquisition, representation and user interface methods for the expert systems development process. Experiential knowledge, scientific knowledge and a combination of the two sources of knowledge has been used to perform the diagnostic task.

Particular emphasis has been posed on the on-line expert system paradigm for technical systems. In this case the main characteristics of the technology as well as a detailed description of specific expert system applications of the last years for the on-line fault detection process have been illustrated. In addition, difficulties and main problems of each technology regarding the diagnostic process for technical systems have been discussed and future directions of the research in these systems have been also highlighted.

Current trends include coupling of these diagnostic techniques in order to produce more effective tools. The new trend for the realization of fault diagnosis is the implementation with cooperative functions that are also distributed in network architecture.

In conclusion, this paper emphasises in expert systems development for fault diagnosis in technical processes. The main characteristics of each technology as well as the difficulties and the problems arising in expert systems development have been underlined and specific expert system paradigms have been presented. Future directions of the research in these systems have been also highlighted.

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