



# **BEST-based diagnostic systems for industrial plants**

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## **Abstract**

A number of industrial diagnostic systems have achieved an expert system status in that they have achieved expert-level performance. Indications are increasingly positive that these methods will scale up for large expert systems for large industrial plants. A variety of general tools for building expert systems are now available, but only a few of them provide all the facilities needed for efficient development of diagnostic systems for large industrial plants. Our tool, called BEST (Blackboard-based Expert System Toolkit), aims to provide all the necessary infrastructure for diagnostic system development, including hybrid knowledge representation language to describe both structural properties (causal relations, inheritance and abstraction hierarchies) and behavioral characteristic (i.e. functionality), compilation techniques to support rapid inference, a wide array of inference control and search strategies, hypothetical and explanatory reasoning, etc. To prove BEST's suitability for the diagnostic task, we will use a real world application in the aluminum industry. We will also show in this article how a structural model and compiled heuristic knowledge can be combined in a diagnostic task.

## **1 Introduction**

Although AI plays a very minor role in industrial automation today, within a decade it can be expected to become one of the drivers of industrial automation. Manufacturing, that used to be labor intensive, is becoming data and knowledge intensive. Though industrial automation offers several unique and fertile areas for AI research, diagnosing malfunctions is among the dominant applications of AI and expert system technology today. The complexity of the industrial process



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and the need to quickly and accurately diagnose problems does suggest an expert system would be appropriate for this domain. The key to expert system design involves capturing and applying knowledge acquired from the engineers, troubleshooters and plant operators. Expert systems strategies and capabilities for diagnosis have been evolving continuously. Most of the earlier diagnostic applications involving expert systems technology have been either rule-based or model-based. Contemporary diagnostic systems use more powerful new techniques, based on a synergistic combination of the above mentioned techniques, enhanced with probabilistic information, learning from experience, explanatory reasoning, hypothetical and approximate reasoning, etc. They offer a heuristic approximation with a much faster decision time, and they are able to cope with incomplete, inaccurate and volatile data. Although some of these aspects of knowledge-based technology, important for the diagnosis applications, have yet to reach full maturity, a few significant applications are already in practical use, with several more on the way to completion. An expert system that deals with jet engine malfunctions has been developed. Another expert system is under development for the Electric Power Research Institute to diagnose problems with large gas turbines used by electric utilities. SRI International, together with Ontario Hydro, a Canadian power utility, developed a system for the diagnosis of electric power generator problems, etc. Some of these expert systems might be able to outperform the human expert.

An analysis of the development process of intelligent diagnostic systems has emphasized the role of an adequate tool for assisting and automating the process. Most of the commercial expert system shells pay little attention to the problems of embedding intelligent systems in real-world environments, such as an industrial plant. The intelligent system is usually seen as a standalone software element, often with its own dedicated processor designed especially for the AI task to maximize performance. Acquisition of data from other systems was difficult and often time consuming. Recently, the needs of embeddedness have been recognized and integrating techniques such as external software calls, database interfaces, sophisticated user interfaces, built-in data filtering techniques, and knowledge processing subsystems are becoming standard. Performance problems are being solved by improved inference mechanisms. In this paper we propose an integrated tool called BEST (Blackboard-based Expert System Toolkit) [7] which, owing to its multiparadigm character [9], supports different methods and stages of intelligent diagnostic system construction. We will use a real-world example to illustrate BEST's suitability for this kind of applications and to demonstrate the value of synthesizing model-based and rule-based diagnostic paradigms.

## 2 BEST as a tool for diagnostic systems development

In the literature on expert diagnostic system, the sharp distinctions are often made between model-based and rule-based diagnostic systems, scientific models

and experiential or associational knowledge, deep and compiled knowledge, content and form, etc. Because of the fact that no structural model of the device under diagnosis is used in rule-based systems, they are often referred to as shallow knowledge systems, where rules are used to conclude each possible fault or malfunction of the system. Although current rule-based systems technology has managed to capture the most obvious aspects of human expertise such as high level experiential knowledge or heuristics ("rules of thumb"), many other aspects of knowledge exist that are just beginning to be addressed. These include the use of deeper, more fundamental knowledge, such as structural or connectivity knowledge. In many systems it can be difficult to understand or describe the behavior and function of the system but simple to describe the connectivity. Human diagnosticians are also very good at using structural knowledge to discriminate among alternative diagnoses. Therefore, the sharp distinction between categories has often been criticized, as in [2], where Chandrasekaran states that the depth of knowledge is relative, and that certain "deep" knowledge element might be derivable from yet another "deeper" body of knowledge by additional reasoning. Consequently, recent literature shows an increased interest in combining different models [1, 3, 4, 5]. For example, diagnostic knowledge that helps map from observations to causes often requires extensive searching in the space of causal relationships generated from the structural model. In summary, we believe that the synthesis of various paradigms is starting to generate considerable mutual benefit and, in the long run, we anticipate the emergence of a combined approach in which the current separation between different paradigms disappears.

Of particular benefit for diagnostic knowledge encoding, inference and explanation is BEST's ability to integrate different programming paradigms [9], to blend qualitative and quantitative approaches, to allow a wider array of techniques for handling incomplete and imprecise knowledge and data (probabilities, certainty factors, fuzzy sets) [7]. Each type of knowledge involved in industrial plant diagnostics (deep knowledge of the structure and connectivity of the device under diagnosis, causal relations, alarms, criteria for dangerous situations, functional knowledge, experiential knowledge, etc.) is represented and used in a way that seems appropriate to that type of knowledge, thank to BEST's hybrid knowledge representation language Prolog/Rex [8]. The experiential portion, embedded in Prolog/Rex rules, provides the structure to the diagnostic process, while the fundamental portion, expressed in terms of Prolog/Rex concepts, provides the structure of the device itself. The diagnostic hypotheses are generated through empirical associations (heuristics) acquired from the experts (plant operators). These heuristics can be considered as shortcuts through the functional model, i.e. they represent compiled versions of the deep diagnostic knowledge, formalized using one among five types of Prolog/Rex rules. Structural knowledge consists of terms corresponding to physical properties of the device. The device being diagnosed is usually

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described in terms of components, relations between components, and some sort of behavioral description of components.

When a complete model of the system cannot easily be found, BEST's hypothetical reasoning paradigm offers a technique for simultaneous explorations of alternative models, induced by alternative initial assumptions about nondeterministic parts of the system [7], [8]. BEST's *context* mechanism represents a set of facts that are entailed by the assumption expressed in terms of BEST's *hypothesis* facility, which helps in differentiating between actual facts and those that have only been assumed to be true. Using this, BEST can generate alternative interpretations of the object structure, and various possible sequences of system operations, and evaluate in parallel each possibility.

The task of generating the hypothesis set for the detected symptoms is inductive in its nature i.e., requires the application of a data-driven (forward chaining) reasoning strategy. The task of discriminating among different hypotheses usually uses a backward-chaining strategy to check each hypothesis' consistency based on knowledge acquired from the outside world and on structural knowledge. BEST supports both reasoning strategies (data- and goal-driven) [10].

Human diagnosticians often try to convince themselves that a diagnosis they have arrived at makes sense by constructing causal stories to support the diagnosis. It is also essential for the expert diagnostic system that it can explain and justify a suggested diagnosis. BEST provides the means of generating explanations (both HOW and WHY types), responding either with a trace of the system execution history or with a customized explanation text.

### 3 An example of BEST-based diagnostic system

We successfully constructed and operationally tested a knowledge based diagnostic system for the main motion reducer in a bauxite-ore mill in aluminum industry, that finds the causes of faults and gives a corrective action advice. Moreover, the general framework that we designed as a side effect of the concrete diagnostic system development (skeletal diagnostic system) offers a guideline for developing of any other on-line diagnostic expert system, and a baseline from which to derive more sophisticated diagnostic system including alarm filtering, prioritisation, etc. The framework enables supplementing of deep structural and causal knowledge (model-based paradigm) with compiled (shallow) empirical knowledge (rule-based paradigm), which is quicker to use, since the speed of a pure model-based system decreases with the number of components. By using shallow knowledge (heuristic rules), especially at the higher level of models hierarchy, we avoid having to model the system in too much detail. Moreover, some empirical diagnostic knowledge encoded in production rules would be difficult to implement in purely model-based system. The advantages of model-based approach have been used for systematic coverage of all plausible device faults and their propagation, speeding up the

whole disturbance analysis. The system captures an expert's operational knowledge (embedded 90 complex rules, organized in 5 knowledge sources) and uses it in a way that emulates human problem solving. Operational procedures formulation is close to natural language and therefore easily understood when presented to the user by explanation subsystem. In this section we will describe this illustrative example in detail.

An acquisition system collects measurements obtained by on-line instruments from main motion reducer components (oil temperatures, oil levels, shock vibrations, etc.), which together with visually observable data (oil leakage, for instance) and data obtained from the chemical laboratory (the presence of metal chips in oil), represent the input data for our diagnostic expert system. Using these data, the expert system is able to determine fault probabilities for each unit, and then to find a critical path (or all paths) that leads from a component specified by user to a leaf component (a concrete component, i.e. an abstract component which is not further decomposed, see Fig. 1).

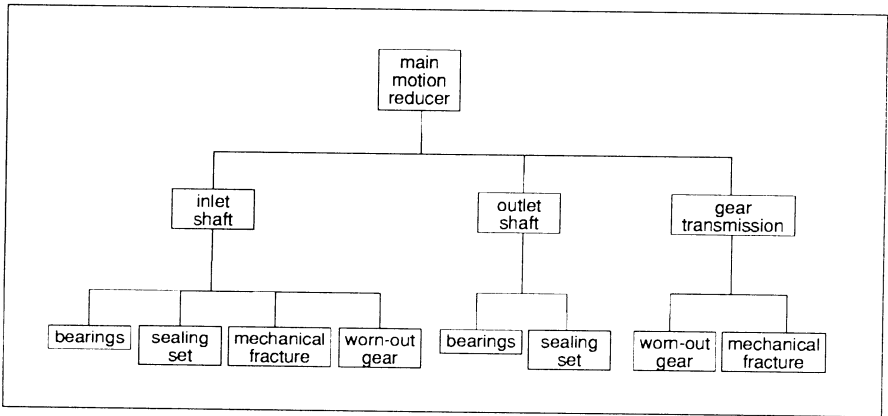


Figure 1: Main motion reducer hierarchy.

Each of the components from the main motion reducer hierarchy is represented by one *concept* in Prolog/Rex [8]. These concepts are hierarchically organized, using two user-defined relations, *consists-of* and its inverse *part-of*. The relation *consists-of* has the inheritance property, which gives rise to multiple inheritance links.

Concepts contain slots that describe characteristics of mill components needed for the fault probability evaluation. Data used as an input for the expert system determine slot values for leaf concepts, while other concepts inherit all the slots from the concepts lower in the hierarchy. If multiple inheritance links

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cause conflicts, then Prolog/Rex *demons* are used to specify which slot value will be inherited.

Procedural knowledge is organized within five modules (“knowledge sources” in blackboard terminology [7]): *input*, *probabilities*, *paths*, *screen\_output*, and *file\_output*.

The *input* knowledge source passes the data obtained by the acquisition system and data entered by the user, to the global data repository (global blackboard [7]). These input data will be used by the *probabilities* knowledge source to estimate fault probabilities for each component. When the probabilities are determined, the *paths* knowledge source finds a critical path (or all paths) from a component defined by the user to a leaf subcomponent. The *Screen\_output* knowledge source prints the located critical path (or all paths) on the screen, while the *file\_output* knowledge source writes the recommended maintenance action into the file.

In order to avoid sharp boundaries between temperature, and shock vibration ranges, we have defined six fuzzy sets: *low\_temp*, *medium\_temp*, *high\_temp*, *small\_vibr*, *medium\_vibr*, and *high\_vibr*. The corresponding membership-grade functions are presented in Fig. 2. We use the maximum membership-grade value to classify a temperature or shock vibration in the corresponding fuzzy set. Using these classifications and information concerning oil level, oil leakage, and the presence of metal chips in the oil, we are able to describe fault probabilities for each component as *small*, *medium*, or *high*.

BEST's truth maintenance capabilities [6] are used to generate a context tree on local blackboard *paths*. This context tree must be used to determine a critical path (or all paths) within the *paths* knowledge source. To each context within the context tree corresponds one component, and to the root context corresponds the component specified by the user. If a main motion reducer is determined, then the context tree corresponds to the main motion reducer hierarchy. Each leaf node contains a path (of components) from the root node, and fault probabilities for each component included in this path. The paths are sorted according to their criticality and written onto the global blackboard.

The *paths* knowledge source must find the paths sorted in order of descending criticality. Within the *paths* knowledge source we use the *best-first* search strategy so that the context tree is generated and examined according to the sorting rule. As a heuristic-evaluate function we use a function that returns a fault probability for a component that corresponds to the current context. Starting from the root context, the contexts corresponding to *high* fault probability components are generated first, then those with *medium* fault probabilities, and finally those with *small* fault probabilities. The described method of context tree generation enables us to find a critical path and to sort all other paths according to their criticality.

After the expert system finishes its work, we can use the HOW-type explanation to describe how fault probabilities are evaluated by the *probabilities* knowledge source. The explanation for a component also gives the possible

roots for such fault probability, and the recommended maintenance action. To each rule within the *probabilities* knowledge source, an importance, that corresponds to fault probability, is attached. By tuning the level of detail, a user can get the explanation only for the components with *high* fault probability, or for the components with *high* and *medium* fault probability, or for all the components.

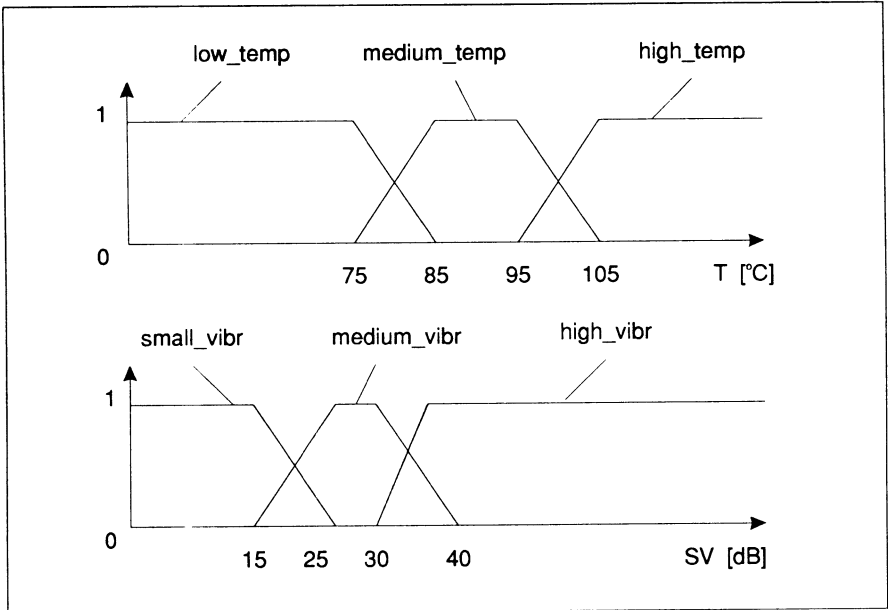


Figure 2: Membership grade functions.

Thank to the explanation capability, our expert diagnostic system could be used as a training aid for operators. Besides, knowledge-based technology in general, and BEST in particular, offer an easy way to add, remove and modify operational knowledge, therefore giving rise to continuous performance improvement of our diagnostic system.

## 4 Conclusions

The diagnostic process requires knowledge that facilitates mapping from observations (symptoms) to diagnostic hypotheses, and knowledge for proving or rejecting alternative hypotheses. At least two kinds of knowledge are used by most real-world diagnostic expert systems, and we will refer to these as structural and heuristic knowledge. The structural knowledge (i.e. knowledge



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about device topology) usually in symbolic form, specifies which entities are associated by what kind of associations. Rules as “rules of thumbs” are heuristic associations between symptoms and causes for generating diagnostic hypotheses. Expertise of this experiential type was contrasted with the deep, structural knowledge, which is supposed to be based on scientific laws (first principles) underlying the domain. Our diagnostic expert system, built using BEST tool, has demonstrated the value of synthesizing structural and heuristic knowledge. Incorporating heuristic information into a model yields computational benefits; exploiting knowledge about structural hierarchy and localized causal relationships constrains search. This synergy not only overcomes a practical difficulty encountered in a pure model-based approach, but also introduces the truth maintenance system ensuring the diagnosis consistency.

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