

# Knowledge-Based Diagnosis System of Machine Tools

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## Abstract

*This paper outlines the development of a knowledge-based expert system for diagnosing machine tool failures. The complexity of machine tool failures and the trouble shooting procedures are deployed. The diagnostic knowledge is acquired from analysis of the troubleshooting and repair reports as well as from interviews with diagnosis engineers. The knowledge base is built using the object oriented modeling. The inference mechanism mainly based on backward reasoning, the flow of diagnosis process guided by the expert system, and the user interaction are explained with an example. A test run of the developed prototype system, developed with a commercial expert system shell, shows the feasibility of local problem solving without help of a service person sent from the machine tool maker.*

**Keywords:** expert system, knowledge base, object model, machine tools diagnosis

## 1 Introduction

In an environment of today's ever increasing competition, a manufacturing company needs to make full use of its manufacturing facilities and thus shorten the manufacturing lead time in order to meet the customer due dates. It requires not only an effective management of operations but also maintaining the optimal condition of the manufacturing system. In case of machine failures the company should be able to isolate the causes as rapidly as possible and to take appropriate corrective actions so that the MTTR (mean time to repair) be kept minimal.

Machine tools for processing materials are one of the most important elements in a manufacturing system. Troubleshooting of modern machine tools equipped with sophisticated electronic as well as mechanical components is so difficult that it requires a lot of experience and knowledge, and thus generally depends on the diagnosing persons from machine tool makers.

The character of machine tool, being capital investment goods unlike consumer products such as household electric appliances, makes it expensive and almost impossible for a machine tool maker to run a vast service network enough to support their customers quickly. An unmanned diagnosis system to which the users can have access at all times and get help in case of a trouble occurrence could be an efficient alternative[1].

Diagnosis in its general sense includes monitoring and supervision of machine operation as well as finding out the causes of a trouble. The objective of the former is to recognize any possible abnormal condition early and prevent machine failures opportunely by keeping track of the processes. Many previous works have been done on this problem, and remarkable achievements have been made in the last years. They can be classified as either condition-based or model-based[2][3]. On the other hand, efforts to analyze causes of a trouble and suggest solutions are rarely found.

This paper addresses the diagnosis of machine tools in its narrow sense focusing on the fault systematics and the relationship between symptoms and causes. Conventionally, machine diagnosis has been made using fault tree analysis or decision table technique, where the troubleshooting paths must have been predetermined. The advantage of these approaches is the simplicity in use and the visibility of the problem complex, while they are not easy to maintain. Anyway, they provide the basis for more advanced ones like rule-based or case-based reasoning, which seem to be promising in solving the cause and effect relationship type problems[4][5][6]. Some of the related researches suggest a new possibility of applying the diagnosis system in a server-client environment, i.e. remote diagnosis. It performs the diagnosis tasks based on the information supplied through internet from the user at a remote site, and sends the results back [1][7][8][9]. The premise is, of course, that an efficient diagnosis server being able to identify the causes of a failure is provided.

This paper describes a knowledge-based expert system for diagnosing machine tool failures, which is developed for a CNC machine tool maker.

## 2 Diagnosis of machine tool failures

Failures occurring in machine tools are so diverse that even classification is not easy. However, they can be roughly grouped into four categories – no operation, malfunction, inaccurate machining, and the others. No operation means that a component of the machine tool is not acting, while malfunction means an abnormal movement of a machine element. Inaccurate machining means inferiority such as bad surface roughness or occurrence of unwanted taper. The frequency distribution for each group is shown in Figure 1, which has been taken from the service statistics of a machine tool company. It indicates that the most frequent trouble is no movement of a machine element such as automatic tool changer, spindle, or hydraulic chuck.

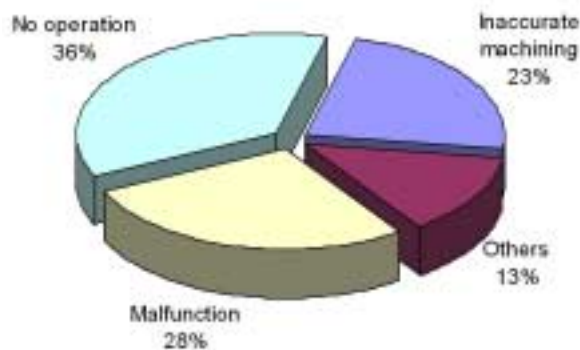


Figure 1. Classification and frequency of troubles.

Diagnosis is a reasoning process to analyze the cause and effect relationship beginning from the symptom, and to find out the origin of the failure. Difficulty in identifying the causes has been attributed to various factors like system complexity, inaccurate information, and lack of adequate troubleshooting tools. In order to form the basis for rational troubleshooting, the possible causes for each trouble should be listed up first, and then the logical failure-cause relationships are to be explored stepwise into more detail. For that purpose it is essential to understand the diagnosing expert's way of thinking. Figure 2 shows an example of diagnosis workflow for inaccurate machining case. At the occurrence of a taper on axis-symmetric cylindrical surface, NC program, machining parameters, diagnosis number(DGN) are sequentially checked until the ultimate cause is localized. If no cause can be found in the control unit, the backlash of lead screw, the alignment of table, spindle, tail stock, and tool post, etc. are examined in that order. Thus, the diagnostic knowledge has been acquired from analysis of the troubleshooting and repair reports as well as from interviews with diagnosis engineers. An excerpt of the knowledge base built is shown in Figure 3

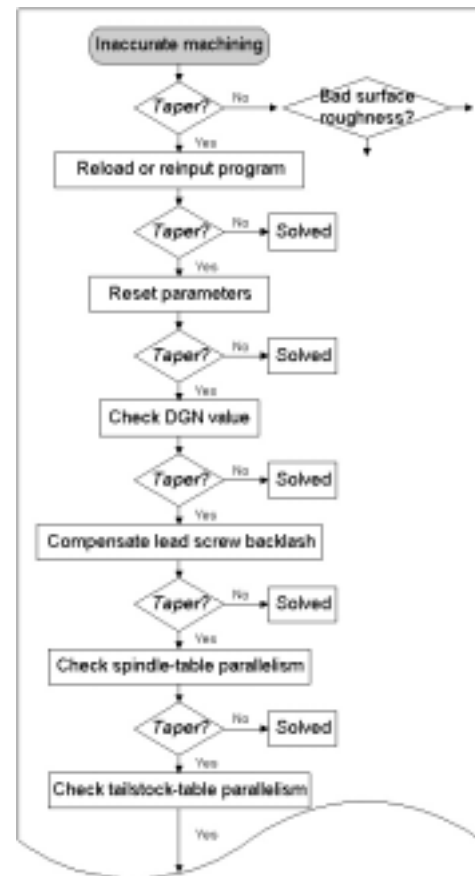
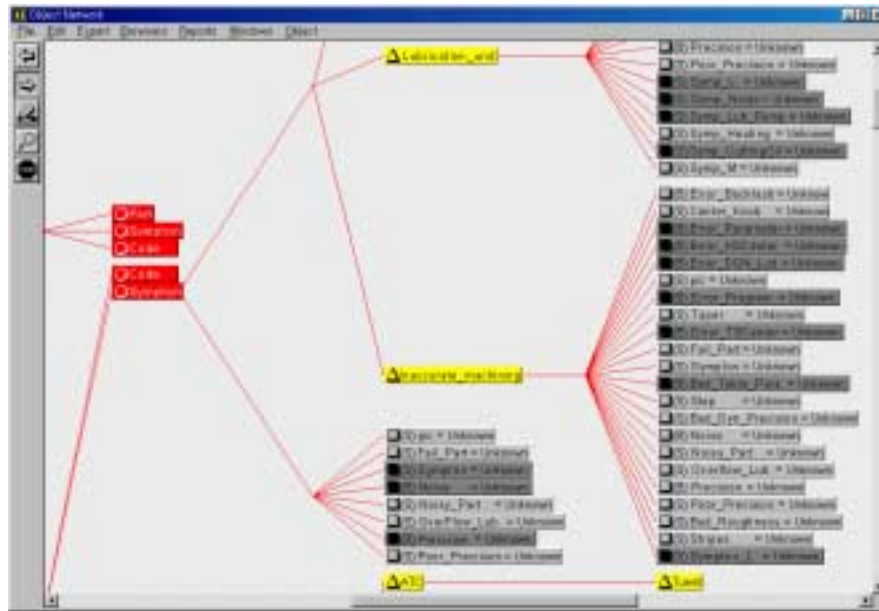


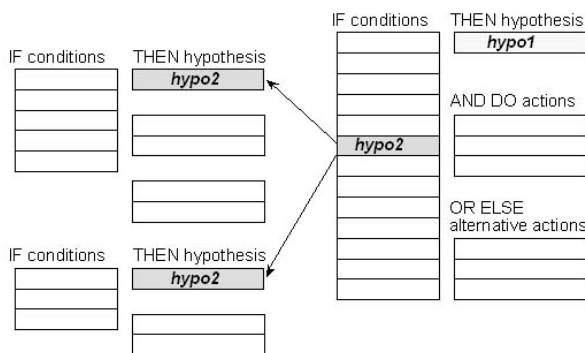
Figure 2. A typical example of troubleshooting workflow.

## 3 Object-oriented representation of the diagnostic knowledge

The object-oriented approach is a good match to the machine tool diagnosis problem for a couple of reasons. Firstly, the physical configuration of a machine tool, usually represented in a BOM (Bill of Materials), shows a hierarchical structure, which gives a natural object-class hierarchy. According to the product structure, the cause of a failure is propagated from an original source to a higher-level assembly. Secondly, the diagnostic logic also has a hierarchical structure reflecting the functional interaction of the components. The diagnosis can be regarded a reverse tracking process of the failure propagation. As shown in Figure 3, the diagnostic knowledge can be represented in an object network, which is natural for the class inheritance features. As the highest-level object the class *Failure\_Symptom* is generated. It has sub-classes such as *Malfunction*, *No\_Operation*, and *Inaccurate\_Machining*. The properties like *Taper*, *Stripes*, *Roughness*, etc. are again assigned to *Inaccurate\_Machining*.



**Figure 3.** An excerpt from the diagnostic knowledge base.



**Figure 4.** Reasoning mechanism in backward chaining.

The diagnostic knowledge is represented in the form of production rules using a commercial expert system shell. A rule is composed of conditions, hypothesis, actions, and optional alternative actions. The hypothesis is a kind of object representing the conclusion of one or more rules. The class structure itself acts as a pointer to a set of objects, with data held by the structure formed by associating a property with each object. This structure is represented by the form *class\_name.property\_name* and is known as a slot. Classes thereby provide a way to search through lists of objects in order to identify which objects meet a specific condition, which is called pattern matching. It also enables the maintenance of failure occurrence statistics by updating the assigned property for rule frequency in accordance with the pattern matching results.

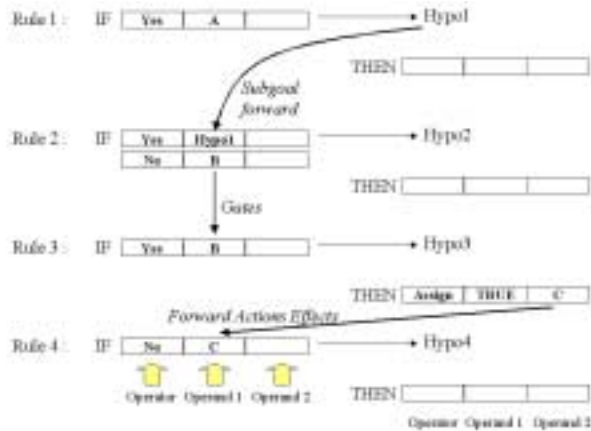
In the backward chaining which is predominantly used for diagnosis problem, reasoning proceeds from a goal trying to match the known facts. It is based on the

evaluation of the hypotheses. The backward reasoning mechanism is illustrated in Figure 4. Let the goal be hypothesis *hypo1*. To evaluate *hypo1* of the rule with unevaluated condition, *hypo2* which itself is a condition of the rule must be verified to be true. The system tries to find one or more rules with *hypo2* as the hypothesis. Once a rule with *hypo2* as its hypothesis is found, the conditions in the rule leading to *hypo2* are evaluated before finishing the evaluation of the conditions which caused the backward chaining to occur.

In the system developed, some more inference search mechanisms like *Subgoal forward*, *Semantic gates*, and *Forward actions effects* are used (Figure 5). *Subgoal forward* is a consequence of investigating subgoals as opposed to a terminal hypothesis. It consists of not only exploring the backward chaining associated with the subgoal, but immediately thereafter placing on the agenda the hypotheses of the rules in which subgoal is involved in a data. An important feature is that subgoal forward events are queued and evaluated as soon as the current rule has been completely evaluated.

*Semantic gates*, or simply *Gates*, are structure-based inference mechanism which accounts for the opportunistic insertion of hypotheses on the agenda. Gates are generated during the evaluation of the conditions list of rules. When any new slot is evaluated in the conditions of a rule, the inference engine checks to see if any other rules also have this slot in their conditions. If any target rules have this slot in their conditions, the inference engine tests the value of particular conditions which include this value. If the condition is TRUE, the associated hypothesis is put on the agenda. In other case, the hypothesis will remain

UNKNOWN rather than being evaluated to FALSE. While *Gates* pre-evaluate the target condition and only place the hypothesis on the agenda if the condition is TRUE, *Forward actions effects* are non-selective. This means they place on the agenda any hypothesis whose conditions have a slot that has been affected by the actions list. Thus it may queue hypotheses even though the condition involving the modified slot might be FALSE.



**Figure 5.** Various inference mechanisms.

Let us consider the case of inaccurate machining. The inference engine searches the rules in order to prove if the slot value of *Hypo\_Failure* is true. The condition can either be given by the user or be determined by the outcome of firing other rules. In this example, it is assumed that the symptom *Inaccurate\_Machining* is selected. Objects in the class *Failure\_Symptom* all have the property *Symptom*. The system evaluates the condition and identifies all the slots of *Failure\_Symptom.Symptom* with the value *Inaccurate\_Machining*. As a result, a list of objects for use by the right hand side actions is generated. If the type of inaccurate machining is taper occurrence, which is to be given by the user, the value *Taper* is assigned to *Inaccurate\_Machining.Symptom* slot. Then, the related rules are fired according to the sequence described in Figure 2 to get the value of *Inaccurate\_Machining.Taper* slot. An example of the final reasoning shows the value assignment *Inaccurate\_Machining* in *Failure\_Symptom.Symptom*, i.e. *Symptom* slot of the *Failure\_Symptom* class, *Taper* in *Inaccurate\_Machining.Symptom*, *Headstock\_Center* in *Inaccurate\_Machining.Taper*.

#### 4 Knowledge-based diagnosis system of machine tools

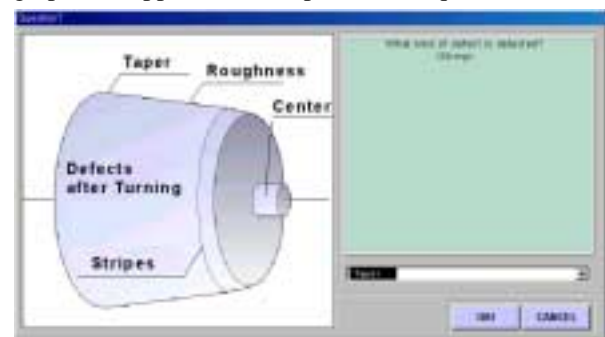
Using the knowledge base built based on the data and know-how of a CNC machine tool manufacturer, an initial implementation of the diagnosis expert system

has been made. The main components of the system are knowledge maintenance module, knowledge base uploading module, diagnosis module, and reporting module. The diagnosis module, core of the system, provides the functions like symptom entry, knowledge base search and rule firing, query and input processing, and corrective action processing.



**Figure 6.** Screenshot of system main menu.

From the initial GUI(Graphical User Interface) as shown in Figure 6, users can select the knowledge base, start diagnosis, modify knowledge base, or retry reasoning. The knowledge base is uploaded according to the selected machine tool type and the diagnosis method – symptom-based or alarm-based. Diagnosis process begins with the selection of the symptom group, for instance “inaccurate machining”. With this given hypothesis the system performs the inference to find the original cause. When the slot values during the reasoning cannot be obtained by the knowledge base search, they must be input from the user, guided by the expert system. The question handler in charge of processing questions and answers provides a user-friendly interaction environment. Through the help of graphical support and comprehensible questionnaires,



**Figure 7.** Question handler window for inaccurate machining.

the user can input the meaningful value without difficulty. For instance, a symptom can be correctly selected from the possible defects as displayed in Figure 7. In a similar way, the object properties are determined in order.

Considering again the example shown in Figure 2, let us suppose that the cause of the trouble "taper occurrence" is backlash in the lead screw. Figure 8 shows the question handler indicating the necessary work instructions for backlash check. A typical example of the final reasoning result looks like Figure 9, which shows the necessary corrective actions together with question and answer history.



**Figure 8.** Question handler indicating the actions for backlash check.



**Figure 9.** Example of a final diagnosis result showing the corrective actions and Q & A log.

## 5 Concluding remarks

A knowledge-based expert system for diagnosing machine tool failures has been developed. The diagnostic knowledge has been acquired from the analysis of troubleshooting and repair reports as well as from the interviews with diagnosis engineers. The object-oriented approach is used to implement the

knowledge base using a commercial expert system shell. The inference mechanisms such as backward reasoning, hypothesis forward, semantic gates, and forward action effects are used for reasoning. Experiences obtained from test runs for a CNC lathe seem quite promising. Provided a more extensive and reliable knowledge base is implemented, an unmanned support of the machine tool users in troubleshooting will be possible.

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