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TOWARDS A REALTIME KNOWLEDGE-BASED SIMULATION SYSTEM FOR DIAGNOSING MACHINE TOOL FAILURE

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ABSTRACT

A framework for diagnosing and characterizing the failure propagation of various components in a CNC machine tool using real time knowledge-based simulation is discussed. The input data necessary for conducting simulation is obtained from a knowledge base structured using frames. Preventive maintenance and sudden failures are modeled. The implemented system provides an integrated environment for the maintenance supervisors to obtain early warnings about the expected failure times of different components and the stoppage time of the machine tool.

1. INTRODUCTION

Manufacturing engineers are often concerned with issues relating to product design, process planning, and physical transformation of raw material into final products. However, there is less concern for maintaining and utilizing manufacturing equipment. It is this segment of the manufacturing environment where great strides can be made toward improved productivity and product quality. Further, the capital investment in a computer integrated manufacturing (CIM) environment is very high, and the cost of this investment accrues regardless of whether the machines are running or not running. By keeping the machines up and running at a high level of quality, performance and reliability, an increase in return on capital investment can be obtained. Machine tools can be kept operational and producing high quality output by several means including the following: (1) Diagnosing the failure process and introducing policies to alleviate these failures, (2) Standardizing and certifying the quality and reliability of the machines, (3) Cultural changes in the worker and workplace through educational programs and (4) Adoption and adherence to a well structured preventive maintenance program.

In this paper, we describe a framework for characterizing and diagnosing the failure process of a CNC machine tool. The framework integrates on-line data collection devices such as sensors and gauges, a knowledge base structured using frames, a data base manager, and a manufacturing simulator. The framework utilizes realtime, knowledge-based simulation (RTKBS) concepts. Only the implementation details of the simulation model and the knowledge bases to predict machine tool failures are included in this paper. Results of a machine tool failure simulation are presented to illustrate the operating principles of the RTKBS.

2. MACHINE TOOL FAILURE PROBLEM

Typically, a CIM environment consists of several CNC machine tools and inspection stations. These are linked by computer controlled material handling systems and other auxiliary devices [Kochan 1986]. A CNC machine tool consists of a series of inter-related hardware components such as gear boxes, motors, hydraulic pumps, filters and valves, tools and fixtures, CNC control devices, and electrical supplies. Active and passive signature analyses are performed to measure temperature, vibration, fluid levels, displacement, and forces to characterize component failures. These failure characteristics affect the performance of the machine tool, possibly leading to its total stoppage. Some of the reasons for machine tool downtime include: (1) Undetected collisions due to operator error, subsystem failure, (2) material handling failure, (3) in-process gauging errors, (4) bearing and spindle failures, (5) no or improper repair or service, (6) no data collection, and (7) power outage [Rathmill 1988]

Consider a CNC machine tool composed of several components that are susceptible to breakdown. Whenever a breakdown occurs, a specific component or several components are repaired. Further, preventive maintenance is periodically carried out on these components. The quality level (Q) of the component depreciates over time and improves to a certain extent after each maintenance or repair. The life of the component ends when it is no longer economical to repair or maintain it.

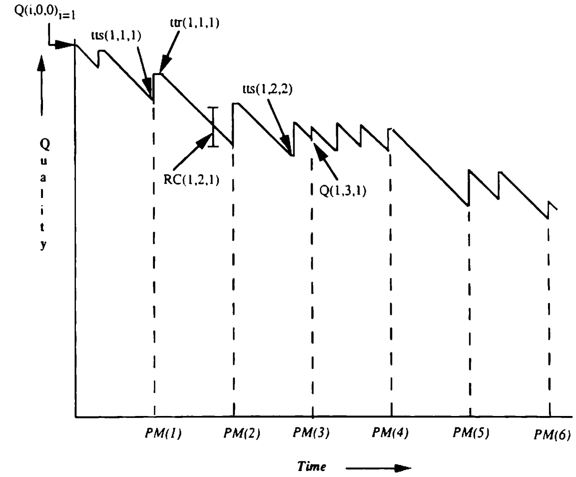

Figure 1. Quality Versus Failure Process (Component i)

Figure 1 shows the changes in the quality level [$Q(i,j,k)$] of the ith component, say, a roller bearing, over time. The quality level is at $Q(i,0,0)$ when the component is new or replaced after failure and beyond any further repair (j=0 and k=0). During the life of a component, two kinds of events occur that cause the stoppage of a machine tool. These events are scheduled or preventive maintenance (k=1) and sudden failures (k=2) of one or more components. These events occur periodically and at random, and are denoted by j, where j=0,1,2,3,....n. The following notation is defined to characterize these events:

$Q(i,j,k)$ = Quality level of the *ith* component after the *jth* occurence of the *kth* event
$tts(i,j,k)$ = Time to stoppage of the *ith* component after the *jth* occurence of the *kth* event
$ttr(i,j,k)$ = Time to repair the *ith* component after the *jth* occurence of the *kth* event
$RC(i,j,k)$ = Recovery in quality level of the *ith* component after the *jth* occurence of the *kth* event

An example for each of the items listed in the notation is shown in Figure 1. As component1 ages and is in use, preventive maintenance (PM) and sudden failures (SF) occur. For instance, the notation tts(1,1,1) indicates the time to stop for component1 due to PM performed for the first time, and tts(1,2,2), indicates the time to stop for component1 due to SF occuring the second time and so on. Similarly, ttr(1,1,1) is the time to repair the first component due to PM performed for the first time. Q(1,3,1) is the quality level of the first component after the third occurrence of scheduled maintenance and RC(1,2,1) is the recovery in the quality level after the second PM is completed on component1. The recovery in quality level of a component, RC(i,j,k), after each PM or repair activity is not considered in this paper.

3. RESEARCH IN FAULT DIAGNOSIS

The problem of machine tool maintenance has been approached from several directions. Models can be constructed that provide statements such as the probability that component X will fail in the next Y hours of operation is Z (based on some distribution of time to failure). A step above probabilistic models are statistical models that provide confidence intervals. Both these models fail to pinpoint when failures will occur. In addition, they treat components in isolation rather than as parts of a larger system. Quite advanced from the probability/statistical approaches is the use of expert systems to diagnose failures and recommend procedures to correct those failures. An example is IN-ATE [Cantone and Caserta 1988; Azegami and Fukoka 1988]. IN-ATE is a commercial software specifically designed for troubleshooting electronic or mechanical systems. A schematic block diagram with the connections among the components of a system is the input for IN-ATE. I-CAT, a revised version of IN-ATE, has been extended to apply universally to all electrical, electronic, and mechanical assemblies. The revised version emphasizes the economic aspects of fault diagnosis. An example of its use for troubleshooting components on a complex circuit board has been discussed in [Kennett and Totton 1988]. Existing tools such as IN-ATE and I-CAT perform off-line fault diagnosis. Their application is more as a post mortem analysis than as a predictive mechanism. However, in order to improve maintenance effectiveness and the utilization of manufacturing resources, an integrated system that can monitor, measure, analyze, and characterize the failure phenomena in a machine tool is needed. Such a system can be used to predict machine tool failure, thus reducing downtime and maintenance costs.

4. RTKBS DESIGN AND IMPLEMENTATION

An integrated environment for providing early warnings to the maintenance supervisors about the expected failure times of different components and that of a machine tool, a realtime knowledge-based simulation system (RTKBS) has been designed and implemented. This section describes the subsystems of RTKBS (see Figure 2) and its operating principles.

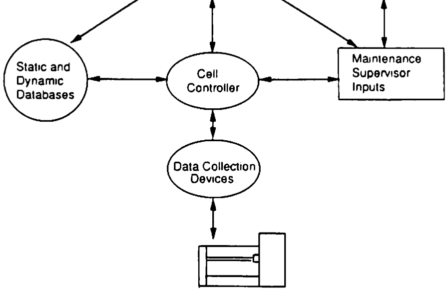

Figure 2. Various Subsystems in RTKBS

4.1 RTKBS Subsystems

The RTKBS system as shown in Figure 2 includes, (1) data collection devices, (2) static and dynamic databases, (3) knowledge bases, (4) simulation models characterizing the failure process of various machine tool components, and (5) a cell controller.

4.1.1 Data Collection Devices

These are sensory devices and in-process gauges to measure and obtain data from the components of various manufacturing equipment.

4.1.2 Static and Dynamic Databases

The static database contains machine tool data, product data, machine quality indices, maintenance resources, and maintenance performance measures. The dynamic database contains information received from the sensors connected to the components of a machine tool either continuously or periodically.

4.1.3 Knowledge Bases

The knowledge bases in the RTKBS system are structured using frames for the following reasons: (1) To provide the data input to the SIMAN experiment frame, (2) To store and retrieve data on failure characteristics and sensory inputs from various components of the machine, (3) To create property inheritance between similar components used within a machine tool of the same type, or among components of several machines, (4) To store and retrieve the results obtained from previous simulation runs to reduce the number of resimulations.

4.1.4 Simulation Model

The failure phenomena of various interrelated components of each machine tool are modeled and stored in the model base using a manufacturing simulation language. The input data associated with each model is obtained from the frames stored as part of the knowledge base.

4.1.5 Cell Controller

The cell controller in the RTKBS is a micro- computer designed to monitor component failure within a machine tool. It interacts with the knowledge bases and retrieves the necessary input data to perform simulation using the model created. Further, the cell controller updates the knowledge bases using the simulation outputs for future use.

4.2 Dynamic Knowledge Bases in RTKBS

Knowledge in RTKBS is represented using frames. Frames are data structures implemented for organizing knowledge into prototypical objects and stereotypical events associated with a specific CNC machine tool. Frames are used to encode knowledge obtained from machine tool specification, maintenance manuals, previous experience, and common practices of people involved in repairing the machine tool.

Each frame consists of a name followed by one or more slots. Each slot can hold one or more links. Each link has an associated value. The most commonly used link names are "value" and "default". A link name can also be a "demon" such as "if-needed", "if-added", and "if-removed". Frames provide a mechanism to build relationships between other frames [Buchanan 1986]. For instance, the slot, "a-kind-of" can be included in each frame to set an inheritance property with other frames. By setting property inheritance between the components (based on their purpose and characteristics) of existing machine tools, we can deduce the failure process and the subsequent repair activities for a new machine tool.

Declarative, procedural and temporal knowledge bases reside within RTKBS. Various frames implemented to be part of these knowledge bases are discussed in the following sections.

4.2.1 Declarative Knowledge Base

The declarative knowledge base includes frames specifying factual information on machine tool characteristics, individual components and part processing. For instance, if we consider a spindle and two bearings as part of a CNC machine tool, then the machine, component, and part processing frames include the following:

Frame0:Machine
(Machine_type (....(machine_name machine_number machine_quantity (component_1 component_2 ....))))

Frame1:Component
(Component (Spindle ((scheduled (cycles machine_time age))
(sudden (TTF TTR ATTF Prob_Indf))..))
(Bearing_1 ((scheduled (cycles machine_time age))
(sudden (TTF TTR ATTF Prob_Indf))..))
(Bearing_2 ((scheduled (cycles machine_time age))
(sudden (TTF TTR ATTF Prob_Indf))..))
(Combo_1 (bearing_1 spindle)
((scheduled (cycles machine_time age))
(sudden (TTF TTR ATTF Prob_Indf))..))
(Combo_2 (bearing_2 spindle)
((scheduled (cycles machine_time age))
(sudden (TTF TTR ATTF Prob_Indf)).)))

Frame2:Part_Processing
(Part_Proc (Part_1 (IAT PT batchsize))
(Part_2 (IAT PT batchsize))
.
(Part_n (IAT PT batchsize)))

In frame1, *TTF* is the time to fail for a component, *TTR* is the time to repair a component, *ATTF* is the added time after which the machine will breakdown due to failure of a series of components (dependent failures), Prob_Indf is the discrete probability value to represent the dependent failure of the component. In frame2, *IAT* is the inter- arrival time and *PT* is the processing time on the machine tool for a part.

4.2.2 Procedural Knowledge Base

Procedures are invoked by the demons implemented to be part of declarative and temporal frames. Again, for a machine tool consisting of a spindle and two bearings, the procedural knowledge base includes algorithms to compute the distributions for time between preventive maintenance sudden failures, and the repair process.

4.2.3 Temporal Knowledge Base

Using the on-line data and the algorithms in the procedural knowledge base, temporal information for each machine tool is obtained. Frames are designed to store data as part of the temporal knowledge base. Again, for a machine tool consisting of a spindle and two bearings, the temporal knowledgebase contains the following frames:

Frame3:Time_between_scheduled_maintenance - TBSM
(TBSM (Spindle ..)(Bearing_1 ..)(Bearing_2 ..))

Frame4:Time_to_perform_scheduled_maintenance - TPSM
(TPSM (Spindle ..)(Bearing_1 ..)(Bearing_2 ..))

Frame5:Time_between_sudden_failures - TBSF
(TBSF (Spindle ..)(Bearing_1 ..)(Bearing_2 ..))

Frame6:Repair_Time_due_to_sudden_failure - TPSF
(TPSF (Spindle ..)(Bearing_1 ..)(Bearing_2 ..))

Frame7:Proportion_of_time_sudden_failure_affects_others - PTSFAO
(PTSFAO (Bearing_1 Spindle) p1)
(Bearing_2 Bearing_1) p2)
(Bearing_3 Bearing_1) p2)
.
.
(Bearing_n
(Bearing_3 Bearing_2 Spindle) p3))

Frame8:Signal
(Current_time (Mach_1 Spindle (Signal# 3 On))
(Mach_2 Bearing1 (Signal# 2 On))
.
(Mach_m Spindle (Signal# k On)))

Frame9:Wait
(Current_time (Mach_1 Spindle (Wait# 1 On))
(Mach_2 Spindle (Wait# 2 On))
.
(Mach_m Spindle (Wait# k On)))

Frame10:Simulation_run_data
(SRD (Number_of_replications value)
(Total_length value)
(Output_data_file# value))

Data in the temporal frames are utilized by the simulation model to predict the failure of a machine tool. The wait and signal frames are implemented to provide the current status of different components within a machine tool to the maintenance supervisor. The SRD frame stores the simulation experiment data for each machine tool.

4.3 Operating Principles of RTKBS

Figure 3 provides a detailed framework of the RTKBS. The operating principles of the RTKBS are discussed in this section. Suppose that a component in a specific machine tool experiences a sudden failure. A signal is sent through a sensor to the cell controller. The cell controller queries the knowledge base using a forward chain inference engine to determine whether the same type of failure has been recorded previously. If the answer is in the affirmative, then the controller determines the time at which the entire machine tool will stop from the output frames generated by previous simulation runs that are stored in the knowledge base. This information is then transmitted to the maintenance crews and the production supervisor. If the failure has not been observed previously, then the cell controller invokes a simulation model built specifically for this machine tool and stored as part of the RTKBS. The input data for the simulation experiment is obtained from the declarative, temporal and procedural knowledge bases. The outputs from the simulation include the expected failure times of the various components within the machine tool, and times at which the machine is expected to stop. This information is transmitted to maintenance supervisors and stored in the knowledge base for future use. The model validation is performed by comparing simulation results with the actual failures occured over time.

5. IMPLEMENTATION OF RTKBS

RTKBS implementation is currently underway at the Georgia Institute of Technology. The frames and the associated inference engine have been implemented using Common Lisp on a Sun 3/60 workstation. A model using the SIMAN simulation language for a specific machine tool has been built. The modeling phase, the experiment data, and the outputs generated by each simulation run are discussed in this section.

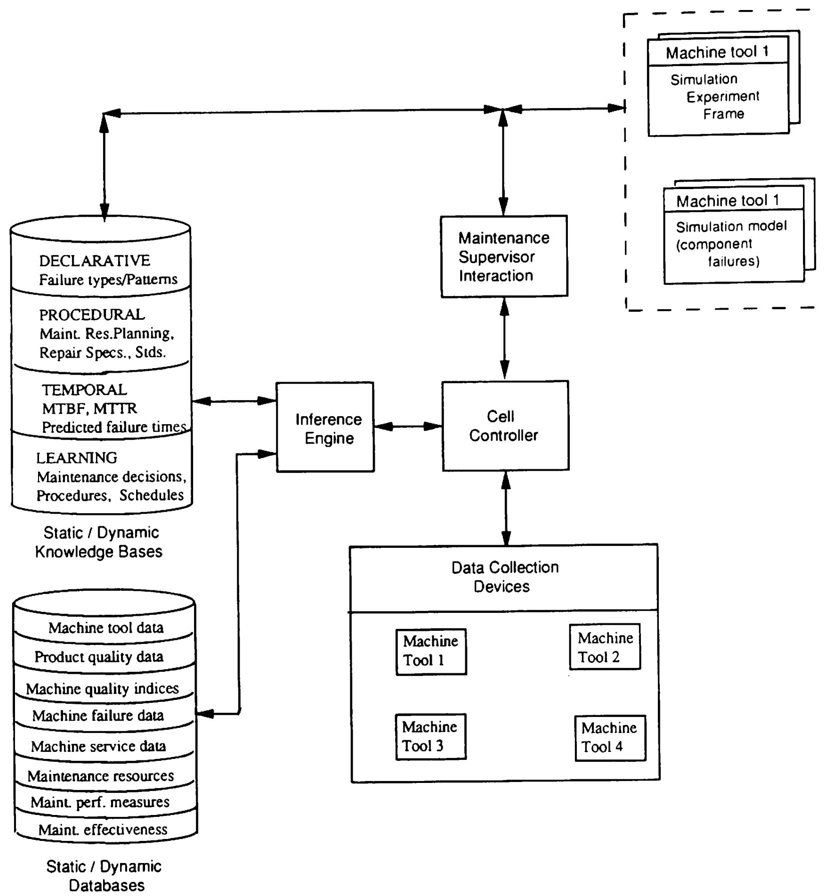

Figure 3. Detailed Framework of the RTKBS

5.1 Modeling Machine Tool Failure

Three major modules have been implemented as part of the simulation model and are as follows:

Module1: Set Up a Manufacturing Environment

Part arrivals, part processing, counting the number of parts produced, the total machining time, and the aging of the machine tool are modeled.

Module2: Failure Process of Spindles and Bearings

Both preventive maintenance and sudden failure for spindles and bearings in a machine tool have been simulated. Preventive maintenance is modeled based on total parts produced by the machine, total machining time, and age of machine tool. Sudden failure is modeled to include both dependent and independent failure processes. An example for dependent failure may be that bearing failure leads to spindle failure followed by machine failure. Whereas, an independent failure is one in which the bearing failure directly causes machine failure.

Module3: Relate Component Failure to Machine Stoppage

Whenever a component fails, this may cause instantaneous stoppage of a machine tool (independent failure) or it may cause other components to fail subsequently (dependent failure). Independent and dependent failures are modeled as follows:

(a) Independent Failure

A signal is sent whenever a component fails, stopping the machine and initiating a repair process. After the repair is complete, a signal is sent to the component indicating that the machine is up.

(b) Dependent Failure

When a component fails, a time is added, after which a related component also fails thus causing the machine to stop. Then a signal is sent to initiate the repair process on all failed components. After completion of the repairs, individual components are signalled that the machine is up.

5.2 Simulation Experiment Data

The input data necessary for the three modules of the simulation model are stored in an experiment file. The failure characteristics of individual components are obtained from the knowledge base and transferred to this experiment file. The experiment file consists of the following:

(a) Sudden failure for all components

- Distribution of time between failure
- Distribution of time to repair

(b) Preventive maintenance for all components

- Scheduled starting time
- Distribution of time to perform maintenance

(c) Components

- Type and quantity
- Relationship between components and machine
- Probability of dependent failure

5.3 Output Statistics

The simulation model is executed using the data in experiment file. The output generated includes the expected time of failure for each component, the expected stoppage time for the machine tool and the expected total time to repair the failed component(s).

The outputs generated by the simulation are utilized by the maintenance supervisor to (1) prepare for upcoming component failure, replacement and repair, (2) order replacement parts and maintenance tools to perform repair, (3) schedule repair crews, (4) warn the production supervisor of an upcoming machine stoppage, and (5) identify all the critical components that are subject to frequent failures and take corrective action.

5.4 An Example Using RTKBS

A simulation model using the SIMAN language has been written for a specific application. The failure process is studied for a spindle supported by two roller bearings mounted on the three jaw chuck of a CNC turning center. Figure 4 indicates the inputs provided by frame0, frame1, frame2 and frame10 stored in the knowledge base and characterizes the failure process of various components of the CNC turning center.

```
Frame0:Machine

    (TURNING
        (....(CNC TURNING CENTER CNC-TC-C1 1)
                    (Bearing_1 Bearing_2 Spindle))))
```

```
Frame1:Component

    (Spindle (...(scheduled (50 60 350 UN(3 4) ))
                (sudden (EX(48) UN(4 6) EX(12) NIL))...))

    (Bearing_1 (...(scheduled (80 72 250 UN(5 6) ))
                (sudden (EX(60) UN(4 8) NIL 0.5))...))

    (Bearing_2 (...(scheduled (100 96 300 UN(6 8) ))
                (sudden (EX(36) UN(5 8) NIL 0.4))...))

    (Combo (bearing_1 spindle)
                (...(scheduled (NIL NIL NIL NIL))
                    (sudden (UN(5 7) NIL NIL NIL))...))

    (Combo (bearing_2 spindle)
                (...(scheduled (NIL NIL NIL NIL))
                    (sudden (UN(6 8) NIL NIL NIL))...))
```

```
Frame2:Part_Processing

    (Part_1 (UN(4 6) UN(2 4) 1))
```

```
Frame10:Simulation_run_data

    (SRD (Number_of_replications 1)
         (Total_length 5000)
         (Output_data_file# OUTPUT_1))
```

Figure 4. Frames from Knowledge Bases for Simulation

The SIMAN model and the experiment files for the CNC machine tool as specified by frame0 are first invoked. The data from frame1 and frame2 are used to configure the experiment file. The model is then executed for 5000 hours as specified by frame10. The results generated during the simulation are sent to an output file. Tables 1 and 2 indicate the time persistent statistics and the number of times the machine tool stopped due to preventive maintenance and sudden failures during 5000 hours of simulated time.

From Table 1, it is inferred that the average fraction of time that the entities wait for preventive maintenance (PM) plus the average fraction of time to receive PM adds up to 1. Similar inferences can be made for sudden failures (SF).

Table 1. Output for Model Validation

Identifier	Average
Utilization (Machine)	0.59
Parts waiting (Machine)	0.37
Entities waiting for PM (Machine)	0.87
Entities waiting to perform PM (Machine)	0.13
Entities waiting for SF (Machine)	0.79
Entities waiting for repair of SF (Machine)	0.21
Entities waiting for PM (Spindle)	0.96
Entities waiting for SF (Spindle)	0.94
Entities waiting for repair of SF (Spindle)	0.06
Entities waiting for PM (Bearing 1)	0.95
Entities waiting for SF (Bearing 1)	0.97
Entities waiting for repair of SF (Bearing 1)	0.03
Entities waiting for PM (Bearing 2)	0.96
Entities waiting for SF (Bearing 2)	0.97
Entities waiting for repair of SF (Bearing 2)	0.03

Thus, Table 1 contributes to the validation of the simulation model. From Table 2, the number of times the machine tool and the components failed suddenly is obtained over a simulated time period. This data can be utilized to determine the mean time between the machine tool stoppages.

Table 2. Number of Failures from Simulation

Identifier	Count
Parts produced	993
Number of Machine stops - PM	131
Number of Machine stops - SF	180
Number of Spindle stops - PM	56
Number of Spindle stops - SF	64
Number of Bearing 1 stops - PM	44
Number of Bearing 1 stops - SF	22
Number of Bearing 2 stops - PM	31
Number of Bearing 2 stops - SF	24
Combined failure (Bearing 1 - Spindle)	44
Combined failure (Bearing 2 - Spindle)	61

The simulation output can be further processed to estimate (1) the times at which various components are expected to fail, (2) the times at which the machine tool is expected to break down during a selected time period, and (3) repair schedules due to preventive maintenance and sudden component failures. Thus, the RTKBS system provides a capability to maintenance supervisors to understand and diagnose machine tool failures in real time.

6. CONCLUDING REMARKS

A framework to diagnose and characterize the failure process of various components in a machine tool using knowledge-based simulation is discussed. The knowledge base is structured using frames. A simulation program has been developed for a specific CNC machine tool by modeling component failures. The input data for the simulation model was obtained from the knowledge base. This depends upon the machine tool and the components whose failure process needs to be studied. The RTKBS provides an integrated environment for maintenance supervisors to obtain early warnings about expected stoppage time of a machine tool. The system also provides the capability to identify the critical components susceptible to frequent failures.

An extention to the RTKBS system is currently underway at Georgia Institute of Technology. There are two directions that the extensions are taking.

In the first direction, the structure and the contents of the knowledge base are being enhanced to consider several machine tools instead of a single machine tool as described in this paper. Two approaches are used in frame design to represent independent and dependent failure process. The independent failure has been represented by decomposing a machine tool into (1) subsystems (electrical, mechanical, hydraulic and control), (2) subassemblies (gear trains, motors, pumps, etc.), and (3) components (spindles, bearings, bushings, leadscrews, etc.). In this case, the frames consist of the distributions of TTF, TTR, ATTF. The depedent failure is represented using a network that provides the relationship between various components. Frames are designed to represent this hierarchy and to store the failure characteristics. This enhancement provides an environment in which the failure prediction can be made for a new machine tool recently installed where no information is available on the expected failure times. Using the frame representation, inheritance property and the failure data recorded previously for all the existing machine tools, the failure characteristics of the new machine tool can be inherited. This information can be used in the simulation model to obtain an initial estimate of TTF, TTR, ATTF for the new machine tool.

The second direction consists of extending the current capabilities of the simulation model to handle several machine tools instead of a single machine tool. For this purpose, a library of simulation models are being built and stored in the model base of the RTKBS. Each simulation model will depict the failure process of a set of interrelated components of a machine tool. Further, rules are being designed to choose the appropriate simulation model from the model base, given a network showing the relationship between components that are critical to the function and operation of a machine tool.

The enhancements to the structure of the knowledge base and simulation model library are being implemented on a Sun 3/60 workstation. The integrated system (with graphic animation) will provide the maintenance supervisor with a capability to determine the expected failure times of various components of a new machine tool. In addition, off-line analyses can be performed using the RTKBS system to study the sensitivity of the simulation input data obtained from frames.

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