A SYSTEMATIC APPROACH TO INTEGRATED FAULT DIAGNOSIS

OF FLEXIBLE MANUFACTURING SYSTEMS

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Abstract: A Flexible Manufacturing System (FMS) is an application of modern manufacturing techniques. Like other manufacturing equipment, the success of a FMS is very much dependent upon its trouble-free operation. It is crucial to monitor all the possible faults or abnormalities in real time and when a fault is detected, to react quickly in order to maintain the productivity of the FMS. Because of the FMS's complexity, the functionally complete diagnosis of a FMS should be based on all the available information and various advanced diagnostic techniques so as to get a satisfactory result. This paper proposes a systematic approach to fault diagnosis of FMS's integrating condition monitoring, fault diagnosis and maintenance planning. An intelligent integrated fault diagnosis system is designed with a modular and reconfigurable structure. The implementation of the integrated diagnosis system is presented in detail. The system can monitor the major conditions and diagnose the major faults of a FMS, and give corresponding maintenance planning as well. The developed system has been applied to an existing FFS-1500-2 FMS in Zhengzhou Textile Machinery Plant and has achieved good results.

Keywords: Condition monitoring, Fault diagnosis, Information integration, FMS

1. INTRODUCTION

With the development of modern manufacturing technology, Flexible Manufacturing Systems (FMS) have become key equipment in factory automation. This kind of manufacturing equipment is being more and more widely used because of its potential to improve the strategic and competitive position of firms. However, such manufacturing equipment is very dependent upon the trouble-free operation of all its component parts. When a fault occurs, it is critical to isolate the causes as rapidly as possible and to take appropriate maintenance action. Typically, when a FMS goes down, only a small fraction of the downtime is spent repairing the machine that causes the fault. Up to 80% of the downtime is spent locating the source of the fault [1]. For this reason, corresponding diagnostic techniques and systems are studied extensively with the application and dissemination of FMS's.

Many diagnostic techniques and systems appear to have been reported in literatures on diagnosis of FMS's. Toguyeni proposes some reasoning mechanisms for the implementation of an on-line diagnostic system [2]. These mechanisms are based on a distributed processing of symptoms that enables the problem of the real-time constraint to be solved. Cheng proposes a model-based approach for automating the fault diagnosis process of a FMS [3]. The approach utilises a fuzzy digraph coupled with worst-first search reasoning for tracing root causes of a system faults. Weck describes several aspects of an on-line integration of a knowledge based diagnostic system in a hierarchical automation structure of a FMS [4]. DeBonneval presents a hierarchical and modular structure for real-time control of FMS's integrating monitoring of process failures [5]. Modularity is obtained by using a basic component – the module – to build the control system. Chang proposes an integrated quality diagnosis approach which models a manufacturing process using Object-Orient Programming (OOP) techniques and imbeds the dynamic shop floor information in the OOP model [6]. The approach alleviates the burden of storing massive diagnostic information for all the parts in a

FMS environment. Milacic developed a model of an expert system for the conceptual diagnosis and maintenance of FMS mechanical systems [7]. Wu presents an approach for dealing with several critical issues that arise in performing the three activities of an error recovery module: error classification, error knowledge representation, and generation of recovery procedures [8]. Especially the execution errors occurring in a manufacturing system are emphasised. Kuo proposes the Coloured Timed Petri Net (CTPN) based Statistical Process Control (SPC) and fault diagnosis models to model the FMSs' SPC and fault diagnosis behaviours [9]. Ye developed a highly integrated system integrating neural networks with a procedural decision making algorithm to implement hypothesis–test cycles of a system diagnosis on tested fault events [10].

All available diagnostic techniques as well as systematic approaches have their drawbacks, all are not absolute and there is a plea for the effective integration of condition monitoring and fault diagnosis, making full use of all the available diagnostic information and knowledge. In addition, in order that it can be generally used and easily transplanted so as to be convenient to disseminate and develop, the designed diagnosis system should have the following characteristics and functions:

- modular, expandable and reconfigurable structure;
- able to measure and process a large amount of analogue and digital signals;
- able to make complex multi-parameter decision;
- with on-line and real time interfaces to the FMS controllers;

The integrated fault diagnosis system presented in this paper is designed and developed to meet this need.

2. A TYPICAL FMS

A FMS mainly consists of seven component parts: tool system, automated production system (machine tool), material transportation system, load/unload station, computer control and management system, and interface. All these parts are interdependent, interrelated and interactive. They complete different tasks respectively so as to achieve the functions of the FMS. These component parts and their interrelationships are shown in Figure 1.

In order to obtain the optimal operation performance and the biggest economic benefits, all the component parts should be well combined and co-ordinated. Meanwhile, the whole system should be highly flexible and automated. Therefore, among these component parts the computer control and management system is the most important, which has close links with the system diagnostics. The hardware of the control and management system of a FMS is generally in the form of three levels, a reference model of which is shown in Figure 2.

In Figure 2, the material flow controller and the machine tool controller are usually implemented by Computer Numerical Controller (CNC) and Programmable Logical Controller (PLC), which directly control machine tools and material transportation system as well as load/unload stations to perform the I/O functions of the whole system. CNC/PLC can exchange feedback and other information with the computer at the upper level. The control level computer distributes the data from the central computer to every CNC and transportation device, and co-ordinates their operation. It can also be used to analyze and evaluate the production status of each machine tool, and produce commands to revise control parameters. The central computer is used to compile source files of part programs into objective files, and is responsible for management, control, making report forms and recording historical data, etc. Thus it can be seen that, the control information is very important to the system diagnostics.

3. MONITORING AND DIAGNOSTIC TASKS OF FMS's

Like the diagnosis of other manufacturing equipment, fault diagnosis of FMS's means a group of special control functions, namely:

- observation of the machine and process condition using on-line sensors;

- recognition of any incorrect event;
- making decisions on the necessary control action;
- analysis of the diagnostic information;
- display and storage of the fault information for maintenance planning and scheduling.

The fundamental task of a FMS is to realize the relative motions among the work piece and the cutting tool and the auxiliary mechanisms setting out the geometric and technological data of a part program [11]. These motions are previously planned by the programmer. An unexpected and catastrophic change of the condition may indicate a machine or process fault.

In general, correct operational behaviour of a FMS may be characterized by a series of state transitions of the equipment used during the manufacturing of a product [12]. These state transitions occur because of the proper functioning of causal agents responsible for the transitions. The state is characterized by discrete and continuous variables.

Discrete state variables are not only binary or digital control signals but also the signals from switching sensors observing the motion of auxiliary and positioning mechanisms. The error-free cycle of these mechanisms is the foundation of automatic operation. The monitoring and diagnostic tasks based on discrete variables are:

- monitoring and diagnosis of the CNC functions;
- monitoring and diagnosis of the integrated PLC;
- supervision of the correct schedule of the cycling operating mechanisms.

Continuous state variables are the sensor signals measuring the physical state of the machine or process. The monitoring and diagnostic tasks based on continuous state variables are:

- monitoring and diagnosis of machining operation;
- indirect monitoring and diagnosis of the most important mechanisms and functional elements of the FMS;
- monitoring and diagnosis of the tools' cutting features.

In addition, in order to realise the fault diagnosis of FMS's, the following aspects should be taken into consideration:

- FMS structure, principle and functions;
- FMS fault mechanisms and regularity of occurrence;
- the relationship between FMS operating state parameters and process state variables.

When diagnosing a specific FMS fault, besides the monitored process status, we should also have some knowledge about what is normal, what is abnormal and how a system fault affects its operation [13]. Meanwhile, in order to automate the diagnosis process, design of an automatic diagnosis system instead of artificial diagnosis is necessary. According to the FMS monitoring and diagnostic tasks, the designed system should be able to diagnose:

- main process related mechanisms (gearbox, spindle motor, spindle bearing);
- feed process related mechanisms (feed drive devices, servo loop, motion coding devices);
- auxiliary mechanisms (pallet exchange, tool exchange, cooling system, lubricating system);
- materials transportation system;
- control system including CNC, PLC and main control system.

4. DESIGN OF THE INTEGRATED DIAGNOSIS SYSTEM

It is necessary to design new, more complex and powerful monitoring and diagnosis systems, due to the rapid development of hardware and software tools and the continuously increasing demands of the industry [14]. The vast majority of FMS's has automatic monitoring available for faults characterized by discrete state signals in their controllers. These discrete state signals indicate the machine operating state, by which further diagnosis can be carried out. These signals can be obtained directly by using an on-line linkage between the controllers and the monitoring and diagnostic system computer (this can also be carried out via several information-technical levels using local area networks).

However, there is little evidence that the process conditions are continuously monitored inside FMS's. Those continuous state variables must be acquired by designing a data acquisition system outside the FMS's. Hence, the hardware of the integrated monitoring and diagnosis system with a modular structure is designed as shown in Figure 3.

In order to automate the condition monitoring and fault diagnosis, artificial intelligence, in particular an expert system, is often used. However, a highly automated and integrated FMS is an integration of very complex machinery and an equally complex computer system. This is limited to not only mechanical parts, but also electronic, hydraulic, software and human elements as well. All these have different fault distributions. A traditional expert system is ineffective for this purpose. Therefore, there is a need for an integrated diagnosis expert system.

Figure 4 shows the software block diagram of the monitoring and diagnosis system. This is an integrated diagnosis expert system also with a modular structure. A large distributed expert system is formed through the integration of several functional modules and the integration of numerical computation and symbolic reasoning, etc. Above these functional modules, there is a special module called a meta-module, which manages and co-ordinates and controls the whole integrated diagnosis system, calls relevant modules to complete corresponding tasks and provides a good environment for man-machine interaction. The models used are described further in [15]

5. IMPLEMENTATION OF THE INTEGRATED DIAGNOSIS SYSTEM

An integrated diagnosis system based on the above design has been developed for a FFS-1500-2 FMS in Zhengzhou Textile Machinery Plant. The FMS has the construction and control and management system separately as in Figure 1 and Figure 2. In the diagnosis system, condition monitoring, database, knowledge base and reasoning engine are four major functional modules. The implementation of these modules is given in this section.

5.1 *Condition monitoring*

Early condition monitoring systems relied on the sensing and processing of a single parameter by a single sensor [16]. This kind of monitoring strategy is simple and has poor usability and often brings about false or incomplete diagnosis. This single-sensor and single-parameter strategy is only suited for the monitoring of simple process with a single condition or infrequently changed conditions.

The processes of FMS's are complex and changeable. All parts associated with these processes are closely related to each other. The processes involve a large number of factors and the relationship between these factors and processes is very complex and to some extent is fuzzy. In these situations, traditional single-sensor and single-parameter monitoring strategies are not effective. Therefore, a fuzzy hybrid strategy with multiple sensors and multiple parameters must be used to extract multiple parameters from those important parts of the FMS. The hybrid analysis and judgement are then carried out so as to reach a significant conclusion from multiple parameters.

5.1.1 *Parameters monitored*

Considering the sensitivity and ease of acquisition, we chose to monitor power, vibration, temperature of the spindle, feed axes in three directions (X, Y, Z), and pressure of the hydraulic oil and pneumatic supply. In detail, the parameters are as follows:

- Power related parameters: voltage (U), spindle drive motor current (I_s), X-axis drive motor current (I_x), Y-axis drive motor current (I_y), Z-axis drive motor current (I_z). Power (P) is calculated by $P=UI$.
- Vibration related parameters: accelerations of the spindle and the three feed axes (X-axis, Y-axis, Z-axis), each in three directions (X, Y, Z).

- Temperature parameters: temperature of the spindle motor (T_s), oil temperature in the spindle box (T_b), temperature of feed drive motors in three axes (T_x, T_y, T_z).
- Pressure parameters: pressure of the pneumatic supply for clamping devices (P_c), pressure of the hydraulic oil for rotating devices (P_r), and pressure of the hydraulic oil for feed drives (P_f).

5.1.2 *Feature extraction*

In order to describe the operating state of the FMS, the monitoring system must be able to extract signals that indicate the essential features of its process status from many available parameters. A common and normalised feature extraction rule is adopted here, which is based on the classification of the signals into slowly changing signals and fast changing signals. For slowly changing signals, an energy related feature such as amplitude, variance or sum of squares is extracted, which is represented as $E(k)$. For fast changing signals, two kinds of features are extracted. They are

- a feature that indicates the instantaneous rate of change of the process status, represented as $\Delta\Phi(k)$;
- a feature that indicates the changing trend of the process status at the moment, represented as $\sum(k)$, such as energy, divergence, distributed matrix and average variance.

Essentially $\Delta\Phi(k)$ uses the status at a preceding time to check the status change at a later time. Suppose $\Phi(k)$ and $\Phi(k-1)$ are parameters indicating the process status at time k and $k-1$ respectively, then

$$\Delta\Phi(k)= \Phi(k)-\Phi(k-1) \tag{1}$$

Generally speaking, $\Phi(k)$ is related to the information at a certain number of preceding times. Suppose $\{x\}$ is the array of signals to be checked, then

$$\Phi(k)=f\{x(k), x(k-1), \ldots, x(k-n)\} \tag{2}$$

$$\Phi(k-1)=f\{x(k-1), x(k-2), \ldots, x(k-n-1)\} \tag{3}$$

$$\Delta\Phi(k)= \Phi(k)-\Phi(k-1) = f\{x(k), x(k-1), \ldots, x(k-n-1)\} \tag{4}$$

If the representations of the common items in equations (2) and (3) are the same, i.e. they are not affected by time, then

$$\Delta\Phi(k)=f\{x(k), x(k-n-1)\} \tag{5}$$

The greater the relative status change is, the bigger $\Delta\Phi(k)$ is. The machining centre is considered to have a significant event if the status change exceeds a fixed pre-set limit.

The auto-regressive (AR) model for the self-adaptive Kalman wave-filter is suitable for the description of the signal features. Its adaptability is well suited to the principles of feature extraction. Therefore, it is used to describe the fast changing signal features. The AR model is

$$X_k = X^t(k)\cdot\Phi(k)+\omega_k \tag{6}$$

where $\Phi(k)=\{-a_1, -a_2, \ldots, -a_n\}$ is the model parameter, $X(k)=\{x(k-1), x(k-2), \ldots, x(k-n)\}^t$ is the sample array, and ω_k is white noise when the average value is 0.

Parameter estimation by the AR model is defined by

$$\Phi(k) = \Phi(k-1) + \sigma_w^{-2}[X_k - X^t(k)\Phi(k-1)]P(k)X(k) \tag{7}$$

$$P(k) = P(k-1) - \frac{P(k-1)X(k)X^t(k)P^t(k-1)}{\sigma_w^2 + X^t(k)P(k-1)X(k)} \tag{8}$$

where $P(k)$ is the co-variance matrix for parameter estimation, and σ_w is the residual.

Therefore, $\Delta\Phi(k)$ can be calculated according to any of the following equations.

$$\Delta\Phi(k) = \|\Phi(k)\| - \|\Phi(k-1)\| \tag{9}$$

$$\Delta\Phi(k) = \|P(k)\| - \|P(k-1)\| \tag{10}$$

$$\Delta\Phi(k) = \Phi^t(k)P(k)\Phi(k) - \Phi^t(k-1)P(k-1)\Phi(k-1) \tag{11}$$

$\|x\|$ represents the norm of “x”.

Another feature, $\sum(k)$, is described by variance.

$$\sum(k) = \sigma^2(k) = \frac{1}{n}\sum_{t=0}^{n-1}[x(k-t) - \overline{x(k)}]^2 \tag{12}$$

where

$$\overline{x(k)} = \frac{1}{n}\sum_{t=0}^{n-1} x(k-t) \tag{13}$$

Here the changing rate of variance is not chosen for $\Delta\Phi(k)$, and the parameter estimation by AR model is not chosen for $\sum(k)$. This is because the process status can be represented more efficiently through different feature parameter composition, and integration of multiple parameters can be achieved.

For those slowly changing signals, the feature is chosen to be

$$E(k) = \frac{1}{n}\sum_{t=0}^{n-1} x^2(k-t) \tag{14}$$

Parameters like current and voltage can also be processed using the same methods for rapidly changing signals. Their features are

$$\Delta\Phi(k) = U(k) - U(k-1) \tag{15}$$

$$U(k) = \frac{1}{n}\sqrt{\sum_{t=0}^{n-1}[x(k-t) - \overline{x(k)}]^2} \tag{16}$$

$$\overline{x(k)} = \frac{1}{n}\sqrt{\sum_{t=0}^{n-1} x(k-t)^2} \tag{17}$$

where n is determined according to the sampling frequency and the cycle of revolution of every axis. It is usually less than the number of the measured signal points within a revolving cycle of a monitored part/component. This parameter as well as the order of the model can be adjusted during real-time monitoring.

In addition, a normalised processing strategy is employed for state changes caused by the shape of the work-piece and the time sequence of the process. Because the time sequence of the abruptly occurring faults is much shorter than the usual process change, a normalised feature parameter $\delta(k)$ is introduced to process $\Delta\Phi$ further.

$$\delta(k) = \frac{|\Delta\Phi(k)|}{\sqrt{[\Delta\Phi^2(k-1) + \Delta\Phi^2(k-2) + \cdots + \Delta\Phi^2(k-n)]/n}} \tag{18}$$

Thus for each monitored part/component, the extracted features include: U, $\sum(P)$, $\Delta\Phi(P)$, $\delta(P)$, $\sum(I)$, $\Delta\Phi(I)$, $\delta(I)$, $\sum(a_x)$, $\Delta\Phi(a_x)$, $\delta(a_x)$, $\sum(a_y)$, $\Delta\Phi(a_y)$, $\delta(a_y)$, $\sum(a_z)$, $\Delta\Phi(a_z)$ $\delta(a_z)$ and T. In addition, the temperature feature T_b, and three pressure features P_c , P_r, P_f are also extracted. In total, 72 features (17×4+4=72) are extracted in the monitoring system.

5.2 *Data acquisition*

The condition monitoring results described above are stored in the database for subsequent diagnosis use. These data form a major part of the database. The database is seen as a dynamic base that is generated and used by both monitoring and diagnosis. Besides the condition monitoring results, the database also contains other two kinds of fault data: signals from the controller (CNC/PLC) and the observed symptoms. Figure 5 shows a diagram of the data acquisition module.

During diagnosis, a threshold τ is set for each kind of feature, which is obtained according to experience or multiple experiment results. If a feature is greater than or equal to the threshold, it is considered to be abnormal, i.e.

$$f_i = \begin{cases} \text{normal}, & f_i < \tau \\ \text{abnormal}, & f_i \geq \tau \end{cases} \tag{19}$$

The signals from the controllers include the machine operating status signals in the CNC and PLC input, output and flag signals. Fault symptoms are obtained from operation in the plant. The status of these controller signals as well as the observed symptoms is 0 or 1, which can be described by a binary function as

$$f(s_i) = \begin{cases} 0, & \text{when the event related to } s_i \text{ doesn't happen} \\ 1, & \text{when the event related to } s_i \text{ happens} \end{cases} \tag{20}$$

Specifically, for controller signals, the status 0 or 1 indicates the current operating state or position of the machine, while for observed symptoms, it indicates the existence of a symptom. If a status of a symptom is 1, it means there is a symptom, otherwise there is no such symptom.

Taking the PFZ1500 flexible manufacturing cell (FMC), a production cell in a FFS-1500-2 FMS as an example, we may have the following data:

- **C***m* — signal in CNC. *m* is not fixed (depends on how many are needed).
- **E***m.n* — PLC input signal. $m \in (0, 127)$, $n \in (0, 7)$;
- **A***m.n* — PLC output signal. $m \in (0, 127)$, $n \in (0, 7)$;
- **M***m.n* — PLC flag signal. $\mathrm{m} \in (0, 255)$, $n \in (0, 7)$;
- **F***n* — feature data extracted from condition monitoring. In our system, n=72.
- **S***n* — observed symptom. *n* varies according to how many symptoms are observed.

5.3 *Knowledge acquisition and representation*

In a fault diagnosis expert system, fault data is the driver of the diagnostic process, while diagnostic knowledge is the grounds of the diagnosis. Only by combining them can the faults and fault reasons be explained. Like other diagnostic expert systems, this system uses two kinds of knowledge: physical knowledge and experiential knowledge. Physical knowledge is also called deep knowledge or principle knowledge. Experiential knowledge is the shallow knowledge or knowledge of experience. There is a large amount of principle knowledge on a FMS. Most of the experiential knowledge is on the basis of the principle knowledge about the machine, and explains the rough fault reasons according to the fault mechanisms. Experiential knowledge just provides optimized routes to the final diagnostic solution, but not the only route. Therefore, in our system we mainly acquire the principle knowledge, combined with auxiliary experiential knowledge acquisition. This not only reduces the difficulty in knowledge acquisition, but also makes knowledge representation more hierarchical.

In the FMS integrated diagnosis expert system, the diagnostic knowledge acquisition include the following methods:

- Knowledge acquisition based on fault tree analysis: Firstly, the machine is decomposed into multiple functional modules. Secondly, a fault tree is built for each module. The top event in each tree is the most critical fault, even if it is unlikely to occur in practice. The fault trees are coded and saved into the respective knowledge bases.
- Knowledge acquisition based on the control information and principles. This kind of knowledge is acquired from the control programs and relevant documents, electrical and hydraulic circuit drawings, etc. They are the description of the logical relationship between the electrical signals for the machine control processes and sequences.
- Acquisition of condition monitoring knowledge which reflects the faults or abnormalities from the condition monitoring point of view. This kind of knowledge is obtained from the monitoring system designers and the domain experts, or summarized from long-term practical experience. This is used to find possible faults or the location of a fault.
- Collection of expertise. This kind of knowledge is also experiential knowledge mainly about the diagnostic behaviour of knowledgeable engineers or domain experts. This may also be obtained from the diagnostic or repair records of maintenance personnel at the site.

In the design of the diagnostic knowledge base, one of the key problems is knowledge representation. In this system, the physical knowledge, i.e. the hierarchical diagnostic knowledge in the form of a fault tree, is represented as structures. The experiential knowledge and condition monitoring knowledge, as well as the causal knowledge between the symptoms and the faults are represented as independent facts or rules. This forms the hierarchy of diagnostic knowledge representation.

The above knowledge acquisition and representation methods are not independent, but interrelated and combined with each other. After being coded this knowledge is stored in the knowledge base. Principle knowledge can help to determine the exact fault position and explain the condition monitoring results. Experiential knowledge can help to rule out some fault classes and the possibility of some fault positions, determine a rough fault area and provide repair measures. The detailed knowledge acquisition and representation is described in Figure 6.

5.4 *Integrated diagnostic reasoning*

The reasoning engine is the kernel of the integrated diagnosis expert system. As mentioned in section 5.3, a diagnostic process is also the combination of fault data and diagnostic knowledge. It is the reasoning engine that performs the function of the combination.

In order to realize integrated diagnosis and simulate the usual fault propagation process of the FMS, the diagnostic knowledge in knowledge bases is divided into three different levels from the reasoning point of view. They are functional knowledge (functional decomposition), principle knowledge (decomposition according to the operating principles) and experiential knowledge (experts' or knowledgeable engineers' experience). All the knowledge bases are in the form of a fault tree, i.e. a functional fault tree, a principle fault tree and an experiential fault or rule tree respectively. During the diagnosis of a fault, a human expert or maintenance engineer firstly locates the faulty functional modules using functional fault trees. He/she then uses the principle fault trees related to the faulty functional modules to find the rough fault causes, and lastly localizes the fault causes with the help of corresponding rule trees. The diagnostic reasoning process in the integrated system is carried out as described in Figure 7.

In Figure 7, the diagnostic reasoning based on the functional fault tree and principle fault tree is performed using the strategy of breadth-first search combined with the failure probability of each node in the fault trees. Whether a node is faulty or not is determined by various signals in controllers and the logic relationship between these signals. Reasoning based on experiential knowledge or the rule tree is more complicated. For rules associated with machine or process condition, reasoning is performed with the help of condition monitoring results, while for other rules, reasoning is performed as a sequential hypothesis-test cycle [17]. In the cycle, a cost-weighted entropy criterion is used to choose the next part of the rule tree to be activated. This entropy criterion helps to select the rule that gives the maximum fault discernment per unit cost in cases where multiple tests might be performed.

Supposing R_{kj} is a node in the k-th level of the rule tree and $R_{k+1,1}$, $R_{k+1,2}$,, …, $R_{k+1,m}$ are nodes in the $(k+1)$-th level, the cost-weighted entropy of node R_{kj} can be calculated by the following equations:

$$H = -\sum_{j=1}^{m} w_j P_j \ln P_j \qquad m \geq 2 \tag{21}$$

where

$$1 \geq w_j \geq 0, \qquad \sum_{j=1}^{m} P_j = 1 \tag{22}$$

The weighting factor, w, is a normalized cost, determined by the ratio between the actual cost of a measurement operation and the maximum of the set of measurement costs for all components at the current rule level. P_j is the probability with that $R_{k+1,j}$ is the cause of R_{ki}, under the condition that the test result of node R_{ki} is known. Cost-weighted entropy is used to select and activate a part of the experiential knowledge base or rule tree. It selects the measurement that will give the most discernment at the lowest cost. That is to say, the entropy of the next rule to be tested must be the minimum.

6. CASE STUDY

The FFS-1500-2 FMS consists of a PFZ1500 FMC, a KBNG85 machining centre (MC) and an automatically guided vehicle (AGV). The PFZ1500 FMC is made up of some functional modules such as tool change, tool-head change, axis drive and hydraulic drive. The axis drive can also be divided into spindle drive, X-axis drive, Y-axis drive, and Z-axis drive. This decomposition is based on fault tree analysis.

On one occasion, the PFZ1500 FMC failed to work because of an unexpected fault. A diagnostic search of the integrated diagnosis system was conducted as shown in Figure 8.

Depending on signals in the controllers and condition monitoring results, the first search through the functional knowledge base (functional fault tree) led to F33 (machining process), which was a terminal functional knowledge node. The principle knowledge base P11 (the principle knowledge base corresponding to F33) was activated at this point and another search through the principle knowledge base (principle fault tree) led to P32 (spindle motor), which is a terminal principle knowledge node.

Then the experiential knowledge base (rule tree) R111 was activated and the cost-weighted entropy was computed for the R211 and R212 groups. The rule with minimum entropy (R311 – mechanical parts) was firstly tested and maintenance personnel were then instructed to check the corresponding parts of the equipment. Nothing was found to be abnormal. Then the rule with second smallest entropy (R312 – motor temperature) was tested to be abnormal. So further diagnosis proceeded to the next level. The corresponding cost-weighted entropy was computed at this level. At this time the rule with the minimum entropy (R422 – cooling system) was firstly tested. In the end, the fault was found to be caused by a blocked cooling oil pipeline. The cooling system could not provide high enough pressure, which stalled the motor drive which led to the malfunction. In any case, the fault was located and the corresponding maintenance action was recommended. After clearing the pipeline in accordance with the prescribed action, the equipment returned to normal operation.

When a diagnostic search proceeds to the lowest level, the rule with the minimum entropy will be tested first, and the rule with next smallest entropy will be tested second, and so on. If a rule at the bottom level shows a fault, then the diagnosis process terminates. Otherwise the system will check if other observed symptoms have been tested before backtracking within the functional and principle knowledge bases.

7. CONCLUSIONS

The research described in this paper has introduced a systematic approach to integrated fault diagnosis of FMS's. The designed system is an intelligent integrated system with a modular and reconfigurable structure The system is capable of the functions of condition monitoring, fault diagnosis, and maintenance planning. The system has been implemented on a FFS-1500-2 FMS but its generic aspects can also be provided as a turn-key solution to other manufacturing equipment.

Future work on this research will focus on refinement of the monitoring and diagnostic algorithm, improvement of the system design and implementation, and investigation of the potential for a learning strategy. It would be ideal to make the integrated system adapt to changes in various monitoring and diagnostic environments. Furthermore, in order to popularize the use of such a system and also to improve the efficiency of the system, it is important to identify a generic strategy/standard to host the integrated diagnosis expert system on the controllers of FMS's.

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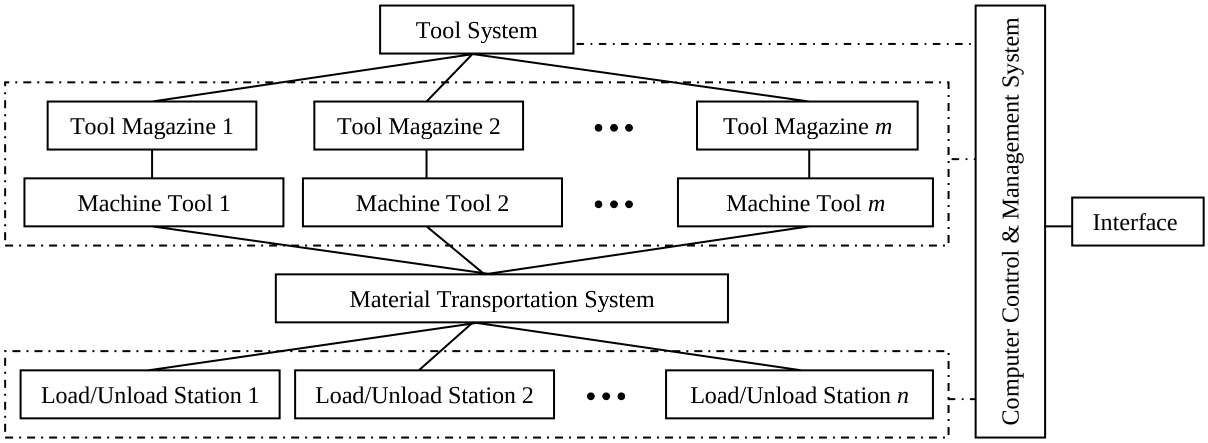


Figure 1. The Construction of a FMS

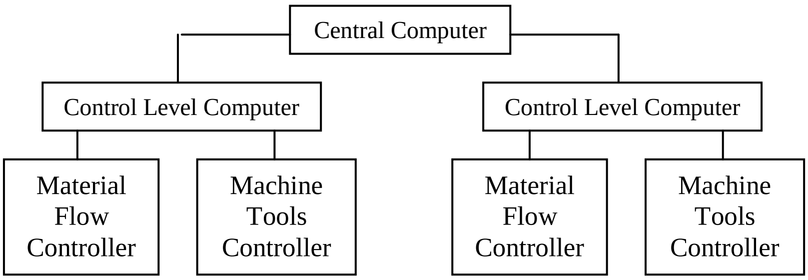


Figure 2. The computer control and management system of a FMS

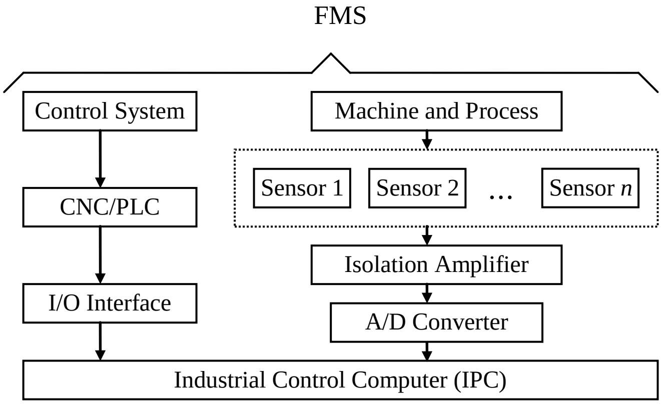


Figure 3. The block diagram of the system hardware

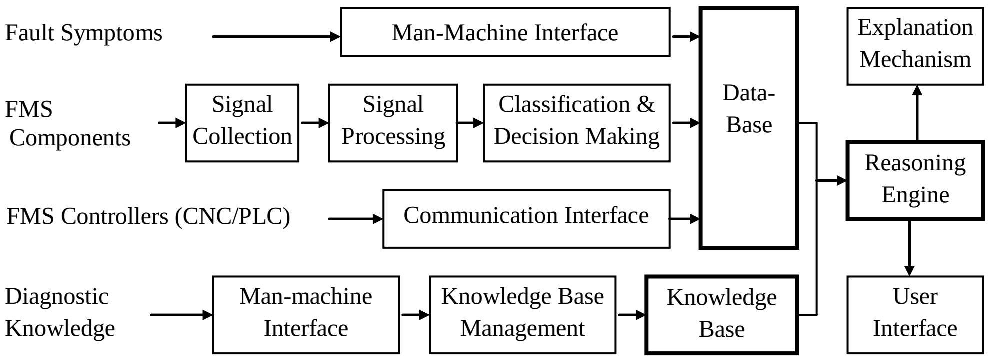


Figure 4 The integrated diagnosis expert system

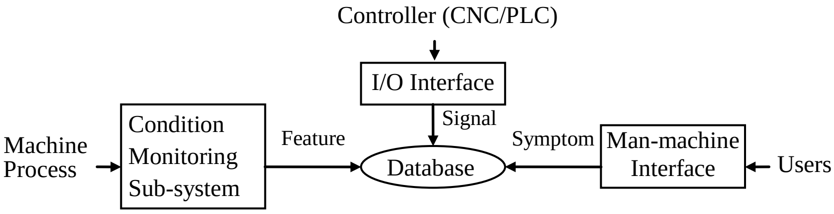


Figure 5. Data acquisition

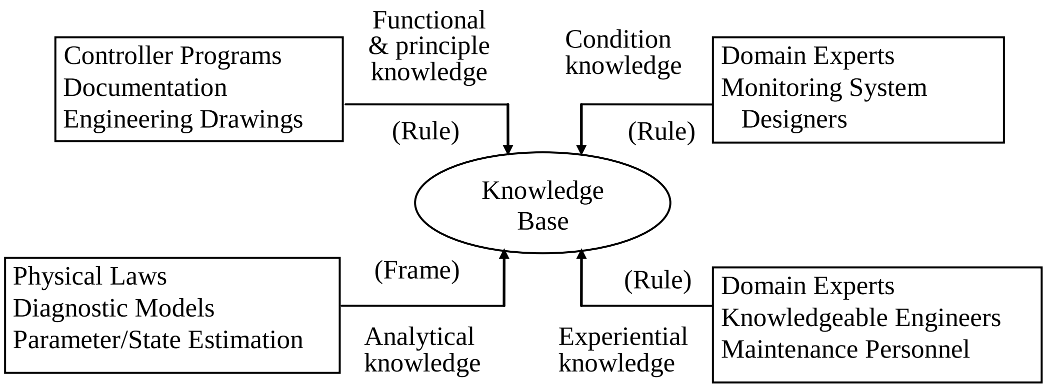


Figure 6. Diagnostic knowledge acquisition and representation

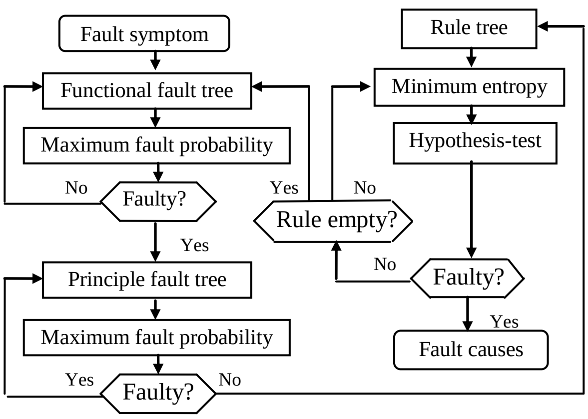
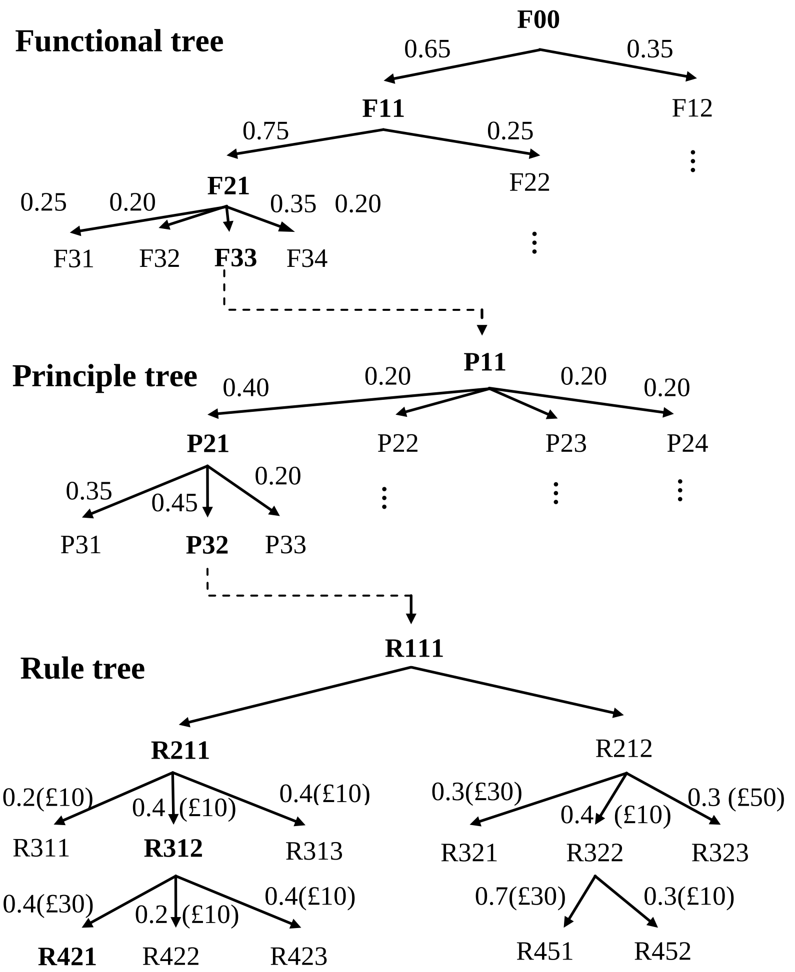


Figure. 7. Integrated diagnostic reasoning process.



Functions
F00: FFS-1500-2 FMS
F11: Machine Tools
F12: AGV
F21: PFZ1500 FMC
F22: KBNG85 MC
F31: Tool Change
F32: Tool-head Change
F33: Machining Process
F34: Hydraulic Drive

Principles
P11: Machining Process
P21: Spindle
P22: X-axis
P23: Y-axis
P24: Z-axis
P31: Spindle Feed
P32: Spindle Motor
P33: Spindle Transmission

Rules
R111: Spindle Motor
R211: Motor Drive
R212: Control Circuit
R311: Mechanical Parts
R312: Motor Temperature
R313: Motor Connection
R321: Circuit Connection
R322: Power Connection
R323: Control Amplifier
R421: Tool Edge
R422: Cooling System
R423: Feed Load
R451: Fuse
R452: Power Switch

Figure 8. Example integrated diagnostic reasoning