Chapter 9

A STUDY OF APPLYING CASE-BASED REASONING ON DIAGNOSING AND MAINTENANCE

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ABSTRACT

Fault-diagnosis is a narrowing down procedure to identify the fault sources according to the symptoms of system broken down. Case based reasoning (CBR) is an efficient method in fault-diagnosis system (FDS) because it can cumulate and reuse the occurred maintenance experience. This chapter reported the methods of diagnosing and maintenance for mechanical systems based on CBR approaches. The methods of identifying fault resources and symptoms of a system are proposed for systematically clarifying the cause-result relationship between the faults and the symptoms. A logical process based on information flow analysis is proposed to quantify the cause-result relationship. The similarities of fault events are calculated by a quantified index for performing case matching in CBR diagnosing. The diagnostic system based on CBR diagnosing is constructed and subjected to an injection molding machine in cooperation with access database. The developed FDS is helpful for maintenance personnel in diagnosing and maintenance of injection molding machines.

Keywords: fault diagnosis, similarity, Case-Based Reasoning (CBR)

1. INTRODUCTION

Maintenance is more and more emphasized for modern engineering system to reduce production cost as well as promote business benefit. The shut-down time of an equipment should be kept as short as possible to meet the needs of effectiveness, especially for an

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automated production system. The actions of a machine shut-down for maintenance usually involve checking, testing, repairing and/or replacing, etc. The possible activities of maintenance while a system is at “down” are shown in Figure 1. These activities each have a time interval associated with it that contributes to the length of the total down time. Among the time intervals, the diagnostic time may be the most significant one in the mean down-time (MDT) because it needs many professional techniques for identifying the problem points. To shorten the MDT, It is useful to develop a systematic method for diagnosing exactly what the problem is and how to fix it based on the collection and analysis of relevant data.

There are many diagnostic methods having been proposed for engineering systems based on various approaches. For example, a systematic approach on fault diagnosis of flexible manufacturing systems was proposed by Hu et al. [1] for integrating condition monitoring, fault identification and maintenance planning. The condition monitoring diagnostic methods have also been successfully applied in rotary machinery fault diagnosing [2]. To treat the uncertainty of the fault information, Tsai et al. [3] reported an evaluated method of system states and reliability based on a combination of Bayesian method and fuzzy signal information. Nguyen and Lee [4] employed a simple genetic algorithm (GA) to evaluate and select the optimized features for induction motor fault classification. The features were extracted from time vibration signals and used for the purpose of diagnosing motor faults. For complex systems, making use of modular, hierarchical architecture to explore the fault causes as well as fault diagnosis tools is a practical method.

Fault diagnosis is a narrowing down process from the system unit step by step into the component or element. The functional block diagram (FBD) of a system top to down can be traced as shown in Figure 2.

The overall plant (subsystem combination) forms the top level, the unit grade the second level and the parts/components the lowest level. Each block denotes a clearly identifiable function, such as a pump, a motor, a shaft, and so on. The diagnostic strategy is to narrow down the hierarchical items step by step based on the symptoms of the problem. The activities of fault diagnosis usually involve symptom definition, fault patterning, knowledge representation, faults inferring, and so on. The best strategy of developing fault-diagnosis system (FDS) is that the information of the fault data as well as available diagnostic knowledge can been completely integrated into the system. Ref. [5] addressed several aspects of CBM approach including definition, related international standards, procedure, and techniques, etc.

Figure 1. Downtime of Maintenance.
Fault diagnostic system is usually developed depending on the types of knowledge representation and function requirements. Several commonly used tools in fault diagnosis are artificial neural networks (ANN), expert systems (ES) and case-based reasoning (CBR). For example, Su et al. [6] proposed a fault diagnosis assistance system where ES was used to construct a diagnostic knowledge base for motorcycle maintenance. Nahvil et al. [7] designed an ANN system for fault prediction in rotating machinery systems. Data from a vibration identification chart consisting of vibration signals for common rotating machinery faults were used to train the network. Wang and Hsu [8] proposed a Web-based CBR knowledge management system for PC troubleshooting based upon integrated cognitive task analysis and hierarchical clustering and ontology techniques. The properties of the ANN, ES and CBR are compared and listed in Table 1.

Focusing on CBR, the basic premise is that we can modify a strategy employed in a previously solved problem to solve a new problem. The CBR system supports the reuse and sharing of expert knowledge and problem solving. It can be used as an alternative to the traditional rule-based and model-based reasoning techniques. The problem-solving experience can be reused to solve the new problem. In the process of analogical problem-solving, the user first needs to receive and recognize the fault attributes. The knowledge system will feed similar past cases that match the terms back to the user based on these attributes. CBR has been successfully employed in a number of different types of problems such as in catering, recipe marking, dispute mediation and criminal sentencing [9]. The advantages of CBR retrieval compared with traditional key-term types of knowledge retrieval for fault diagnosis tasks mean that CBR retrieval could help to improve the performance of traditional fault-diagnosis methods [10]. An applications of CBR for image-based retrieval on polyurethane manufacturing was reported by Segura et al. [11].
Table 1. Comparisons of different diagnosis assistance systems

<table>
<thead>
<tr>
<th></th>
<th>Expert System</th>
<th>Case-Based Reasoning</th>
<th>Neural network</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data constructional method</td>
<td>If/then rules</td>
<td>Trouble-attributes retrieval</td>
<td>Recognition and fast pattern matching</td>
</tr>
<tr>
<td>Data request method</td>
<td>Expert thought process</td>
<td>Old cases</td>
<td>Learning algorithm and weights</td>
</tr>
<tr>
<td>How is it to be solved?</td>
<td>Logical step-by-step fashion</td>
<td>Find a previous similar solution</td>
<td>Recognizing the big picture</td>
</tr>
<tr>
<td>The degree of hardness-easiness to build</td>
<td>Difficult to develop in terms of knowledge acquisition</td>
<td>Easy to build and maintain but slower to diagnosis</td>
<td>Black box and lack of training data</td>
</tr>
<tr>
<td>Data renewal</td>
<td>By hand</td>
<td>By hand</td>
<td>Automatic learning</td>
</tr>
<tr>
<td>Is historical data enough?</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

CBR diagnosing can effectively reduce the training time of maintenance personnel, especially for a novice. It is carried out based on four steps, retrieving, reusing revising and retaining for reusing the previous maintenance experience. Here, CBR method is used to construct a fault diagnosis system (FDS) for injection molding machine (IMM). The similar studies has been presented in Ref.[12]. The possible faults and symptoms of the IMM are clarified by fault tree analysis and information flow analysis. A quantified method for calculating case similarity is proposed for systematizing the diagnostic algorithms of the CBR. The related pages of CBR diagnosing are designed in cooperation with an Access database. The results show that the FDS can provides a good support for maintenance of IMMs.

2. FAULT RESOURCES

Fault information includes fault causes and symptoms of a system at the various levels must first be established at first. An often used method to establish fault causes is by fault tree analysis (FTA). It is extensively applied to construct the hierarchical diagnostic model for maintenance in manufacturing systems [13].

2.1. Fault Tree analysis

Fault tree is a hierarchical structure of faults representing fault occurrence at different levels. It can be determined by Fault Tree Analysis (FTA). FTA is a logical deductive method for hierarchically establishing fault-causes in a system, from the overall system level down to the part/component level. The method is implemented based on the assumption that a fault can be located by analyzing the logical relationship between the system faults and its causes along a fault tree. It has the following characteristics:
(1) FTA can be used to deeply analyze a system fault level by level. It uses clear graphics to describe the internal valid logical relationships between the part/component faults and the system fault.

(2) The fault tree clearly indicates which system fault is related to which part/component, what the relationship is, and how strong the relationship is. It also shows whether a part/component fault will cause a system fault, and if so, what and how great the effect will be.

(3) A fault tree provides a clear illustration for management and maintenance personnel, who may not have participated in the system design, to understand the system properties. This would help to shorten the training time of the maintenance personnel, and therefore cuts down the maintenance expense.

(4) Qualitative analysis using fault trees allows the designer to understand the fault modes and sources of the system, so as to find out weak links in the design scheme, and take corrective measures to remedy them.

Fault trees can be created following the hierarchical structure of the system functions from higher to lower. The hierarchical structure is based upon the principle that a system is comprised of subsystems, the subsystems are made up of modules, which in turn each have their own parts and/or components. Figure 3 shows the structure of a hierarchical system. The fault resources manifesting on the first level are related to the subsystems. The functional and sub-functional modules are related to the second and third levels of the faults, respectively. The parts/components are found at the lowest fault level. Each of the items in the hierarchy is not only the cause of an upper layer event but also the result of a lower layer event. Each corresponds to a real physical structure (based on field knowledge) or the embodiment of a principle.

![Hierarchical structure of a system](image)

Figure 3. Hierarchical structure of a system.
The faults of a Machine can be classified into two categories: sudden faults and gradually induced faults. The gradually induced faults are possibly occurred while machinery is running for a long time. This kind of faults possibly cause to a serious damage if the potential faults didn’t be remedied in time. To avoid serious breakdown occurred, prognostic maintenance is commonly adopted to avoid unexpected failures. It is continuously motoring the performance states of systems so that the faults can be early detected and be solved in time [14].

2.2. Fault Identification

Fault symptoms are the basis of diagnosing since it is direct related to the fault points. Fault symptoms are usually unstructured and are not easily enumerated systematically so as to they are expressed in the form of linguistic descriptions for the state abnormality. A feasible approach to determine the symptoms of a system is to analyze the system’s information flows. System information flows denote the information transformation among functional blocks and can be used to indicate the states of the corresponding function elements. System information flows include three main types, energy flow, material flow and signal flow [15]. The information flows deal with the following:

- Energy: mechanical, thermal, electrical, chemical, optical, nuclear, as well as force, current, heat, and so on;
- Material: gas, liquid, solid, dust, as well as also raw material, test samples, work pieces, end products, components, and so on;
- Signal: magnitude, display, control impulse, data, frequency, stability, and so on.

From the system information flows, the items for all function elements can be easily observed and measured, and fault symptoms determined accordingly. The FBDs of a system (from top to bottom) can be constructed according to the system information flows along with the comprehensive structure of function elements. A recent application of FBDs in fault diagnosing are proposed by the author for providing a helpful methodology for fault identification [16]. The diagnosis trees of the systems are constructed based on a functional block diagram consisting of the function elements and the test points.

Figure 4. Functional block diagram of a mechatronic system.
Table 2. Fault patterns in a mechatronic system

<table>
<thead>
<tr>
<th>Patterns</th>
<th>1 Control signals</th>
<th>2 Output energy</th>
<th>3 Moving velocity</th>
<th>4 Tool position</th>
<th>5 Signal display</th>
<th>Faults</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>Controller</td>
</tr>
<tr>
<td>2</td>
<td>Y</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>Power</td>
</tr>
<tr>
<td>3</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>Mechanism</td>
</tr>
<tr>
<td>4</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
<td>N</td>
<td>Tool</td>
</tr>
<tr>
<td>5</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
<td>Sensor</td>
</tr>
</tbody>
</table>

The function elements of a mechatronic system, for example, may include the control unit, power device, mechanism, tools and sensors (F1-F5). The FBD for this system can be expressed as shown in Figure 4. There are five test points (T1-T5) in this FBD. The symptom attributes for the system are control signals, output energy, moving velocity, tool position, signal display. The deductive diagnosis can be carried out by inspecting the status of these test points. Considering the states of these test points, the fault patterns would be able to be set up as listed in Table 2. The diagnostic activities are to check the status of these test points. For example, a symptom set {Y, N, N, N, N}, where all test points flows are abnormal, except test point 1, indicates power unit failure. Possible fault sources can be identified by comparing the observed symptoms with the fault patterns. Further decomposition of the fault patterns at lower levels is necessary to finally identify the source of the fault.

This narrowing down procedure can be carried out systematically because the information flow of the function elements has a definite sequential relationship. This is because a definite correlation can be set up between the fault patterns and the symptoms. However, in some complex systems (such as mechanical systems), it is not always easy to clarify the sequential relationship of the information flow, due to the parallel or coupled properties of information flow. Ambiguity in the information relationship makes it difficult to narrow down the tasks.

3. CASE BASED REASONING (CBR)

The CBR system retrieves similar cases, and if necessary, adapts them to provide a desired solution when a new problem is given. The solution strategies of CBR are generated by modifying the solutions of the similar cases that are stored in the database according to the described problem structure. This method is easily accepted by users because the reasoning method is similar to the problem-solving strategy frequently used in human thought processes.

3.1. Diagnostic Problems

The fault-diagnosis domain is frequently characterized by ill-defined problems. In other words, clues relevant to solving diagnostic problems may not necessarily be described or
understood simply by assessing their apparent characteristics. Cognitive biases, lack of knowledge and time pressure can all affect fault-diagnosis, and performance is often poor. Maintenance personnel often have a hard time in narrowing down the procedures during diagnosis due to the shortage of domain knowledge, especially for novices.

There is much evidence that novices have difficulty in troubleshooting and diagnosing. The reasons for maintenance novices being hard in diagnosing are listed in following (Schaafstal and Schraagen [17]).

1. Lack of systematic thinking: Novices are not able to adopt functional thinking for problem solving and fault diagnosis. Broad searches of technical documents are therefore necessary to make up for this deficiency.
2. Failure to apply analogical reasoning: Novices do not apply knowledge gained from previous experience to the problems they are currently facing, perhaps because they are not able to, or perhaps because they lack previous experience or knowledge to apply.
3. Lack of systematic fault-diagnosis methods: Though details of relevant systems are available, novices cannot conduct fault diagnoses systematically.
4. Failure to deduce similarities among problems: When a new problem is encountered, the similarity between the current and previous problems can only be deduced through systematic specifications and suggestions.
5. Failure to identify fault symptoms correctly: Novices are often fuzzy about fault symptoms. Their memory loads may increase because of the symptom-masking phenomenon, which prevents the application of fault-diagnosis strategies and weakens their performance.

A feasible approach to overcome some of the above cognitive problems is to use CBR for knowledge representation. It focuses on exploring the experiential knowledge from the past cases which can then be used to carry out fault diagnosis.

![CBR cycle](image)

Figure 5. CBR cycle.
3.2. CBR Steps

CBR solves new problems by adapting successful solutions for similar problems. The appeal of CBR as a problem solving approach lies in its familiarity, where a solution will be obtained based on the solution of similar cases in the past. For example, doctors do not usually start each diagnostic procedure from the beginning. In most cases, they simply recall similar cases, where patients have had similar symptoms, and what treatments those patients received. The present treatment may be modified to meet the specific characteristics of the current patient, such as age, sex, weight and medical history.

The CBR process is illustrated in Figure 5 (Ref.[18]). The CBR is a cyclical process comprising the following actions:

1. Retrieve the case(s) with the greatest similarity;
2. Reuse the case solution to try to solve the problem;
3. Revise the proposed solution if necessary;
4. Retain the new solution.

A new problem (the target case) is matched against the cases in the case-base. The importance attached by the user to various features (indexes) of the case may be used to guide the matching process. One or more similar cases are retrieved from the case-base. A solution suggested for these cases is reused and tested for success. If necessary, the retrieved case(s) are revised to produce a new case, which can then be retained in the case-base.

A CBR system is generally composed of problem data, an action (or adjustment) and result data. When a maintenance engineer is confronted with a new problem he can acquire data for similar cases from the database. The cycle normally requires some user intervention. Most case adaptation in CBR systems is largely performed by the user. In other words, the CBR system acts primarily as an intelligent associative retrieval system. The following key issues need to be resolved for the construction of a feasible CBR system (Watson [19]):

1. Case representation: how to structure cases and what case features should be stored;
2. Indexing: how to assign indices to assist case retrieval;
3. Retrieval: what retrieval algorithms should be used and what is meant by similarity? Techniques for dealing with similarity include nearest neighbor, induction and template retrieval;
4. Adaptation: how can the cases be adapted to solve the current problem?

A fuzzy-CBR approach has been proposed to make the CBR system more user-friendly (Chan [20]). This approach advocates using linguistics variables in fuzzy theory to evaluate the case attributes. A linguistic variable is represented in a natural language form as well as by a fuzzy number. The textual description is intended to help users resolve uncertainty in their valuation of the case attributes. The fuzzy number representation and the associated fuzzy operators are used to calculate the similarity metrics for implementing the case-retrieving mechanism.
3.3. Case Similarities

The first steps of CBR diagnosis are to receive and recognize the fault attributes with the CBR knowledge expression for the analogical problem symptoms. The knowledge system of CBR will feed similar past cases that match the terms back to the user via the similarities of the these attributes.

A case similarity measure is employed in the retrieval process. Query cases are compared with cases stored in the case-base to find the most useful ones. The case-indexing procedure provides an efficient way to search for candidates. The search has a retrieval time which increases linearly with the number of cases and is most effective when the number of cases is fairly small. Users do not need to understand the relationship between the description and the solution since an automatic reasoning algorithm will feed back the proposed solutions.

The case-retrieval algorithm described in the study is mainly derived from the algorithm proposed by Kolodner [9]. The algorithm determines similarities between cases and identifies those with the greatest similarity values

\[
\sum_{i=1}^{n} W_i \times \text{sim}(f^I_i, f^R_i),
\]

where

- \( n \): number of attribute indices;
- \( W_i \): weighting value of the attribute index;
- \( f^I_i \): newly entered case;
- \( f^R_i \): cases in the case library;
- \( \text{sim}(f^I_i, f^R_i) \): similarity between the newly entered case and the case in the case library;
- \( i \): attribute index variable;
- \( I \): identification mark for a newly entered case;
- \( R \): identification mark for an old case.

Determining a suitable set of weights is crucial to success. In the simplest form, users are simply presented with a list of key factors and asked to assign a numerical weight which reflects the significance they place on this attribute relative to the other attributes. These weights can then be used directly in the formula above to retrieve the nearest neighbors.

In this chapter, the weights are determined based on a correlation matrix describing the correlation between the causes and the symptoms of the faults. Assuming that a system has \( m \) causes and \( n \) symptoms, we construct a correlation matrix:

\[
[a_{ij}] = \begin{bmatrix}
    a_{11} & a_{12} & \cdots & a_{1n} \\
    a_{21} & a_{22} & \cdots & a_{2n} \\
    \vdots & \vdots & \ddots & \vdots \\
    a_{m1} & a_{m2} & \cdots & a_{mn}
\end{bmatrix},
\]

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where $a_{ij}$ stands for the possibility of fault $i$ occurring for symptom $j$. The possibility is quantified with 1, 3, 5, indicating Low, Medium, High, respectively. To obtain reasonable correlation values, we refer the FBD of system created by analyzing system information flows. However, the correlation assessment always necessitates more or less subjective judgments, due to cognitive differences. A feasible approach to obtain these values is by combining expert opinions using fuzzy evaluation. For general methods for pooling expert opinions using fuzzy operations.

Based on the correlation matrix, the weightings for various fault types can be defined by

$$W_{ij} = \frac{a_{ij}}{\sum_{j=1}^{n} a_{ij}}.$$  

Here, the weighting values change depending on the fault type. They characterize the symptom attributes for each fault, in accordance with the real fault symptoms.

### 4. Fault Analysis of IMMs

The CBR method is used to develop FDS for Injection Modeling Machines (IMMs) for helping maintenance personnel making a rapid diagnosis for the fault sources based on past maintenance records.

IMMs are used as a case to depicting CBR diagnosing. Normally, fault identification can be a time-consuming process, especially if this type of failure has not happened before or if the maintenance personnel are unfamiliar with the machinery. The IMM transfers the polymeric material (in powdered or granule form) from a feed hopper to a heated barrel. The resin is melted in the barrel and then injected into a mold. In this case, the resin is injected into the mold by a reciprocating screw or a ram injector. The reciprocating screw apparatus is placed inside the barrel. The reciprocating screw is able to inject a small amount of the total shot (amount of melted resin in the barrel). The mold for shaping the plastic is clamped shut...
under pressure with a platen arrangement and is held at a temperature well below the resin’s melting point. The mold is cooled to a temperature that allows the resin to solidify and be cool to the touch. The mold plates are held together by hydraulic or mechanical force. The basic physical structure of the machine is shown in Figure 6 [12].

The possible faults of the machine are determined by FTA method. The decomposition is done according to the tree structure of the system. To simplify the diagnostic process, the fault level during CBR diagnosis is set to function module. This is to consider diagnostic complexity assessed by reviewing the historical maintenance records and face-to-face discussion with maintenance personnel. The possible fault types according to the problem classification for the IMM are listed as follows:

F1: Control unit failure;
F2: Power device failure;
F3: Injection mechanism failure;
F4: Clamping device failure;
F5: Ejection device failure;
F6: Cooling system failure;
F7: Mold unit failure.

The fault symptoms need to be given next. However, the symptoms are described using linguistic expressions which may be irregular and unstructured. To accurately recognize symptoms, the working procedures of the machine are reviewed. They are: (1) Mold closing and clamping; (2) Injection; (3) Holding under pressure and cooling; (4) Material dosing or metering; (5) Mold opening and part ejection. Based on the working procedures and the units for fault classification, the FBD of the machine is laid out, as shown in Figure 7.

In this example, there are eight test points set. The measurements include information on energy, material and signal flows. Reviewing the characteristics of the information flows, the symptom attributes for the machine are defined as follows:

S1: Controller status;
S2: Energy output;
S3: Injection activity;
S4: Mold opening/closing;
S5: Part ejection;
S6: Cooling system function;
S7: Mold temperature;
S8: Injection device temperature.

Discussing an example, provided a problem with the controller, such as being unable to start, signal output abnormalities, overload warnings, malfunctions of the safety door or safety rod, and so on. Abnormal conditions associated with these symptoms each are divided into three levels (0, 1, 2) representing (Normal, Slight and Critical), respectively. The levels are decided according to the complexity of maintenance needed to remedy the fault. For example, the abnormality of a fault which can be repaired by a field operator using only simple tools may be regarded as slight, but if the repair necessitates complicated tools, instruments and professional knowledge, it could be regarded as critical.
(1) Case knowledge

Each case in the case-library describes one particular situation, and all cases are independent of each other. The case structure includes four main parts: problem description, symptom states, fault sources (including causes), and solution strategy. An example of case for IMM maintenance is shown in Figure 8.

Now, a new problem must be solved. Several observations of the current situation and abnormalities caused by the new problem are observed. Note, not all feature values must be known. The observed symptoms of the new problem are shown in Figure 9.

Figure 7. Functional block diagram of an IMM.

Case 1

<table>
<thead>
<tr>
<th>Problem description:</th>
</tr>
</thead>
<tbody>
<tr>
<td>The toggle mechanism for clamping does not work normally.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Symptoms:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Controller state: Normal</td>
</tr>
<tr>
<td>Energy output: Critical abnormality</td>
</tr>
<tr>
<td>Injection activity: Slight abnormality</td>
</tr>
<tr>
<td>Mold opening/closing: Slight abnormality</td>
</tr>
<tr>
<td>Part ejection: Slight abnormality</td>
</tr>
<tr>
<td>Cooling system function: Normal</td>
</tr>
<tr>
<td>Mold temperature: Normal</td>
</tr>
<tr>
<td>Injection device temperature: Normal</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Fault sources:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Power device</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Causes:</th>
</tr>
</thead>
<tbody>
<tr>
<td>The toggle filler oil is inadequate</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Solution:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Add hydraulic oil</td>
</tr>
</tbody>
</table>

Figure 8. Case example.

Problem description:
Material feeding screw cannot be driven.

Symptoms:
- Energy output: Critical abnormality
- Injection activity: Slight abnormality

Figure 9. The symptoms of a new problem.
Here, the other unlisted values of the symptoms are at the defeated value (Normal).

(2) Case Similarities

The correlation matrix for this example is

\[
\begin{bmatrix}
5 & 3 & 3 & 1 & 1 & 5 & 5 \\
3 & 5 & 3 & 3 & 1 & 3 & 1 \\
3 & 3 & 5 & 1 & 1 & 1 & 3 \\
1 & 3 & 1 & 5 & 3 & 1 & 1 \\
1 & 3 & 1 & 1 & 5 & 1 & 3 \\
3 & 3 & 1 & 1 & 5 & 3 & 1 \\
1 & 1 & 3 & 1 & 3 & 3 & 5
\end{bmatrix}
\]

The weights for the various faults can be obtained with Eq.(2). The case similarity can be calculated by revising Eq.(1) as follows:

\[
\sum_{j=1}^{8} W_{ij} \times \left(1 - \frac{s_i^j - s_j^R}{2}\right),
\]

where so is the assessed level of the symptoms. For example, the symptoms for the new problem for case 1 are \{0, 2, 1, 0, 0, 0, 0, 0\} and \{0, 2, 1, 1, 0, 0, 0\}. The resultant similarity between the two cases would be 0.9. Here, the weight set \(W_2\)\{0.15, 0.25, 0.15, 0.15, 0.05, 0.15, 0.05, 0.05\} is chosen since the fault type of case 1 is F2.

The most similar case is chosen in the solution reuse process and this problem solution adapted. The new fault problem is then reviewed by discussing it with the equipment operator. If the cause of the problem is judged to be a burnt-out drive motor the solution is to replace the motor. If this diagnosis proves to be correct, the solution and the new problem form a new case which is stored in the case library.

5. FAULT-DIAGNOSIS SYSTEM (FDS)

The FDS was constructed including two functions for diagnosing and maintenance of an IMMs. One is case management of the case library which includes four operations: adding, deleting, modifying and inquiring. The other one is case-reasoning, where the most similar cases are found, and the case solution reused for the new problem. The related pages of diagnosing were constructed using the ASP programming language. The original IMM maintenance data, including the problems and the solution strategies, were provided by a factory. The data format was revised to conform to the case structure so that case similarity could be computed for progressive case retrieval. The cases were stored in a Microsoft Access database. A page including four functions adding new, deleting, modifying and querying is designed for case management.
Several diagnostic steps and displays are illustrated in the figures.

1. Users input the problem descriptions and the abnormal levels associated with the new problem. The interface of diagnosing is shown in Figure 10. In this example, the new problems are “The material feeding screw cannot be driven”. The appeared symptoms are s2 (critical) and s3 (slight).

2. The CBR diagnostic results are shown in Figure 11. The system automatically computes the case similarity and sorts them in descending order of similarity. In this example, the most similar case would be case 1 which forms the basis of the new problem solution.

3. The problem symptoms and the solution strategies are shown in Figure 12. The page offers the function of modification for the symptoms and solutions according to the retrieval case. It is automatically generated by pressing the adaptation button.

**Figure 10. Case retrieval page.**

**Figure 11. CBR diagnostic results.**
The adapted solution, together with the diagnostic problem, form a new case, which is stored in the case library (the 7th case in Figure 13).

**CONCLUSION**

Fault diagnosing is largely dependent upon the practical knowledge and experience of the maintenance personnel. Making use of past maintenance experience is an efficient approach to shorten the maintenance time. The study reported a FDS based on CBR to perform fault diagnosis for maintenance of IMMs. The fault types and symptoms are derived by the FTA method, which are used to compile an index for retrieving similar cases. The relative importance of the symptom attributes is evaluated based on a symptom to cause correlation matrix. The advantages of the FDS are that similar cases can be retrieved quickly simply by inputting a set of abnormal levels (of symptom attributes) and the solution can be generated.
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accordingly. The CBR diagnosis could be easily applied to other types of equipment just by modifying the attributes of faults and symptoms. The system will become a more and more powerful because the case library is continuously being enlarged depending on the used time increased.

The fault sources and symptoms are the basis of diagnosing. The symptom attributes and the symptom-cause correlations are easily set up by analyzing system information flows. CBR is a technique for solving problems based on past experience by four phases: retrieve, reuse, revise and retain. Fault diagnosis based on CBR can assist in treating ill-defined problems associated with the diagnostic activities. It offers a direct and rapid method for diagnosing faults and generating solutions, and can efficiently simplify the maintenance of a complex system. The weights of symptom attributes have a big effect on the similar cases retrieved and the diagnostic results as well as defining symptom attributes appropriately is crucial in retrieving similar cases and insuring that the proper solution is retrieved.

REFERENCES


