2011 International Conference on Advancements in Information Technology
With workshop of ICBMG 2011
IPCSIT vol.20 (2011) © (2011) IACSIT Press, Singapore

Applying a Case-based Reasoning Method for Reducing Fault Diagnosis's Time During Maintenance

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Abstract. The development of a fault-diagnosis system (FDS) could be helpful in identifying the source of faults before the occurrence of complete system failure. Here we report on such a diagnostic procedure for narrowing down maintenance tasks and shortening system down time. FDS software is developed based on case-based reasoning (CBR) from previous maintenance experience, for a wet magnetite separator machine (WMSM). The techniques of fault tree analysis (FTA) and information flow analysis are used to systematically clarify possible faults and symptoms shown by a system. The possible faults and symptoms of the machinery are set up by analyzing the system's fault trees and its information flow. A logical process is introduced to determine the correlation between the possible faults and the symptoms for computing case similarity while progressing CBR diagnosing and used for calculating case similarity is proposed to formulate the diagnostic algorithms for the CBR.

CBR diagnosing could effectively reduce the training time of maintenance personnel, especially for a novice. Finaly, The front pages of the FDS are created using an ASP program in cooperation with an Access database. The results show that the FDS provides a good support for the maintenance of WMSMs and we can reduce the maintenance time.

Keywords: fault diagnosis, fault tree analysis, case-based reasoning, wet magnetite separator machine

1. Introduction

Maintenance time should be kept as short as possible to meet the high-performance output demands, especially for an automated production system. When a system failure occurs, the maintenance strategy usually involves repairing and/or replacing parts. The main activities take place while the system is 'down'. Each activity has a time interval associated with it that contributes to the length of the total down time. Of these time intervals, the diagnostic time may make up the most significant part of the mean down time (MDT). In order to reduce the MDT we need to develop a systematic method based on the collection and analysis of relevant data for diagnosing exactly what the problem is and how to fix it.

The fault causes and symptoms at the various levels of a system must first be established before narrowing down the fault sources. An often used method to establish fault causes is by fault tree analysis (FTA) [1]. Fault trees can be created following the hierarchical structure of the system functions from higher to lower. The hierarchical structure is based on 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.

Symptom attributes are the basis of diagnosing and are used to determine fault causes. They are usually in the form of linguistic expressions representing the state abnormality, and are unstructured and not easy to be enumerated systematically. A feasible approach to determine the symptoms of a system is to analyze the

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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 [2]. The information flows deal with the following:

a) Energy: mechanical, thermal, electrical, chemical, optical, nuclear, as well as force, current, heat, and so on;

b) Material: gas, liquid, solid, dust, as well as also raw material, test samples, work pieces, end products, components, and so on;

c) 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 most commonly used tools for developing an FDS are artificial neural networks (ANN), expert systems (ES), and case-based reasoning (CBR), depending on the type of knowledge representation required. 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. When a new problem is given, the CBR system retrieves similar cases, and if necessary, adapts them to provide a desired solution. This method is easily accepted by users because the reasoning method is similar to the problem-solving strategy frequently used in human thought processes. In this study, CBR is used to develop a FDS for reducing maintenance time.

2. Applying CBR Method For WMSM

2.1. Case-Retrieval Algorithm

In the process of analogical problem solving (with a CBR knowledge system), users first need to receive and recognize the fault attributes. Based on these attributes, the knowledge system will feed similar past cases that match the terms back to the user via the CBR reference algorithm.

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 that 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 [3]. The algorithm determines similarities between cases and identifies those with the greatest similarity values

$$\frac{\sum_{i=1}^{n} W_i \times sim\left(f_i^I, f_i^R\right)}{\sum_{i=1}^{n} W_i} \tag{1}$$

where *n* is the number of attribute indices, W_i is the weighting value of the attribute index, f_i^I is the newly entered case, f_i^R are cases in the case library, $sim\left(f_i^I, f_i^R\right)$ is the similarity between the newly entered case and the case in the case library, i is the attribute index variable, *I* is the identification mark for a newly entered case, and *R* is the 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 that reflects the significance they place on this attribute relative to other attributes. These weights can then be used directly in the formula above to retrieve the nearest neighbors. In this study, 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

$$\left[a_{ij}\right] = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix}$$

Where a_{ij} stands for the possibility of fault i occurring for symptom j. The possibility is quantified with 1, 3, and 5, indicating low, medium, and high, respectively. To obtain reasonable correlation values, we refer the FBD of the system created by analyzing system information flows. However, the correlation assessment always necessitates more or less subjective judgments, because of 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, the interested reader can refer to Klir and Yuan [4].

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

$$W_{\mathrm{ij}} = \frac{a_{ij}}{\sum_{\mathrm{j}=1}^{\mathrm{n}} \mathrm{a}_{\mathrm{ij}}} \tag{2}$$

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.

2.2. Fault Sources and Symptoms of WMSMS

The WMSM used in this case study is a part of Separation of magnetite from iron ore used in Gole Gohar Company. If a failure occurs, 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 CBR method is designed to help users make a rapid diagnosis of the fault source based on past maintenance records.

The magnetite iron ore plants poured into the mill after transfer from the mine pit. This mill makes stones into small gravel up to 25 cm in diameter. Then the materials are transported by conveyor to the dry mill where to separate the iron ore concentrate to 500 microns in size. Then the materials filtered by separators in three categories: concentrated, intermediate and waste materials.

Dried concentrate was transferred into the storage silos and Intermediate materials that are still a significant amount of iron concentrate will be transported to the wet mill in order to attract more concentrate and The waste materials are transferred out of Factory. The intermediate materials transfer to elevator by conveyor bar No.132 which there is a motor on top of it to transfer these materials in three silos. After separating concentrate white wet technology then the wet concentrate mixed with dried concentrated and transfer to inventories for sale [5].

For showing the CBR methods in reducing fault diagnostics time we use a block of asset in this factory that we named them wet magnetite separator machine which is shown in Fig. 1.

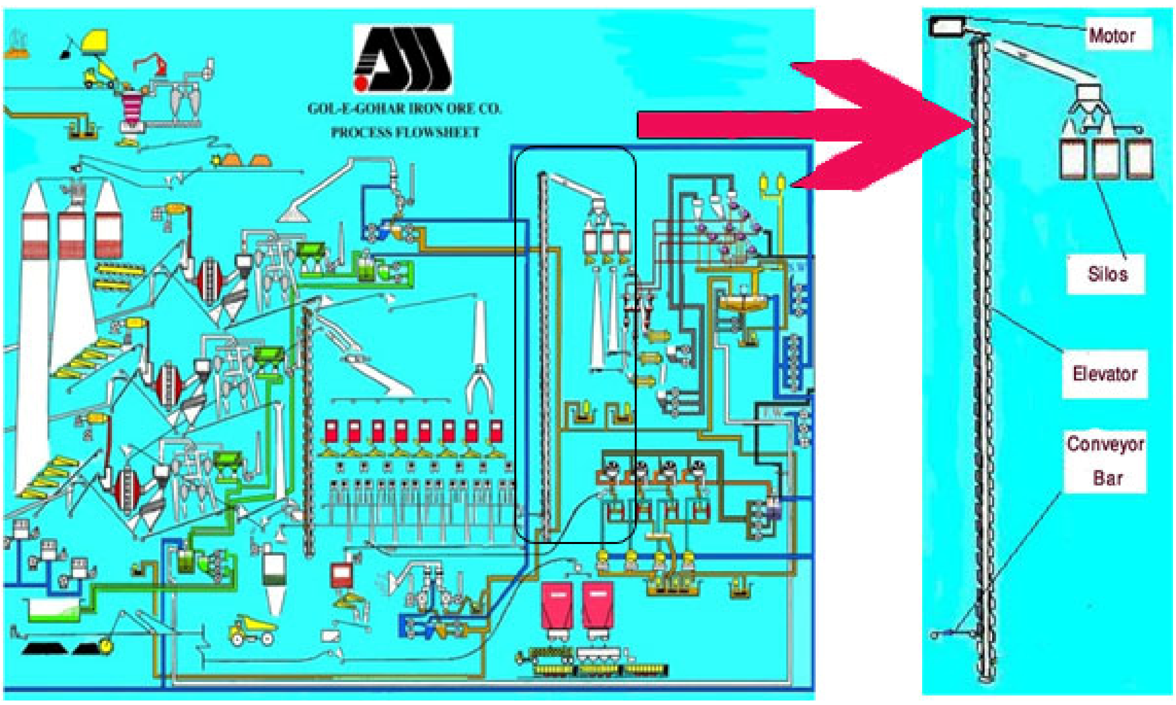


Fig. 1: Wet Magnetite Separator machine

Possible faults with the machine can be determined by using the FTA method. The hierarchical fault structure is shown in Fig. 2. Decomposition is carried out 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. Based on the problem classification, the possible fault types have

$F1$: conveyor bar;

$F2$: elevator;

$F3$: motor;

$F4$: silos;

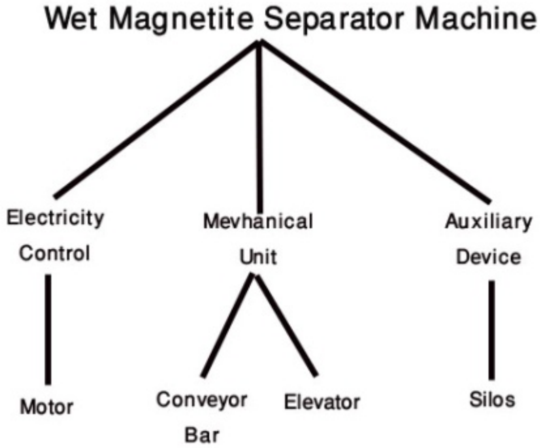


Fig. 2: Hierarchical structure of the possible faults for an WMSM

The fault symptoms need to be given next. Based on the working procedures and the units for fault classification, the FBD of the machine is laid out. In this example, there are four 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:

$S1$: the load of conveyor bar;

$S2$: motor energy output;

$S3$: oil temperature;

$S4$: Silo level.

Let us now discuss an example. Let us say that there is a problem with the motor, such as being unable to start, signal output abnormalities, overload warnings, malfunctions of the conveyor bar or elevator, and so on. Abnormal conditions associated with these symptoms each are divided into three levels 0, 1, and 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 that 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.

2.3. Case Structure

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 a case of **WMSM** maintenance is shown below:

Case 1 *Problem description:*

The elevator is filled.

Symptoms:

a) the load of conveyor bar: critical

b) motor energy output: critical

c) oil temperature: normal

d) Silo level: slight critical

Fault sources: elevator

Causes: loading to much

Solution: elevator evacuation

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:

Problem description:

Conveyor bar is broken

Symptoms:

a) the load of conveyor bar: slight critical

Here, the other unlisted values of the symptoms are at the defeated value (normal).

The correlation matrix for this example is

$$a_{ij} = \begin{bmatrix} 5 & 1 & 3 & 1 \\ 3 & 5 & 1 & 1 \\ 1 & 3 & 5 & 1 \\ 1 & 3 & 1 & 5 \end{bmatrix}$$

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

$$\sum_{j=1}^{8} wij \times \left(1 + \frac{s_j^I - s_j^R}{2}\right) \quad (3)$$

Where sj is the assessed level of the symptoms. For example, the symptoms for the new problem for case 1 are {1, 0, 0, 0} and {2, 1, 0, 0}. The resultant similarity between the two cases would be 0.7. Here, the weight set $W2j$ {0.1, 0.3, 0. 5, 0.1} is chosen since the fault type of case 1 is $F1$.

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 forma new case, which is stored in the case library.

2.4. Diagnostic System

We develop an FDS for the maintenance of WMSMs. The FDS system includes two main functions. 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 is reused for the new problem. The related front pages for diagnosing were constructed using the ASP programming language. The original WMSM 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.

Several diagnostic steps and displays are illustrated in the figures.

1. Figure 3 shows the operational interface for case management.

2. Figure 4 shows the CBR diagnostic results. 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. Finally, the adapted solution, together with the diagnostic problem, forms a new case, which is stored in the case library (the seventh case in Fig. 5).

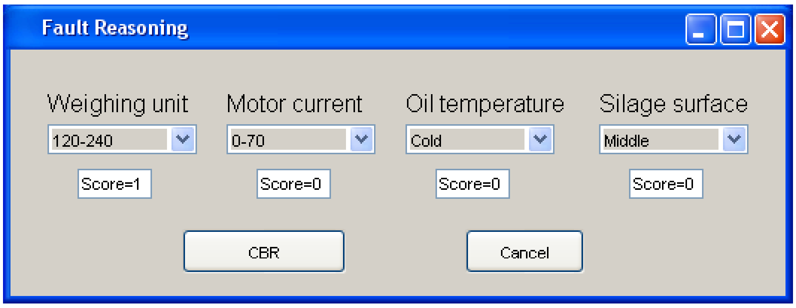
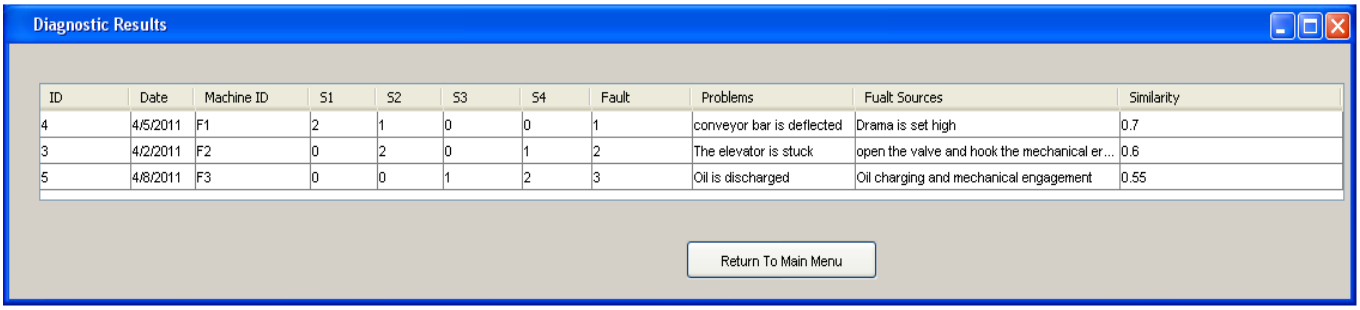
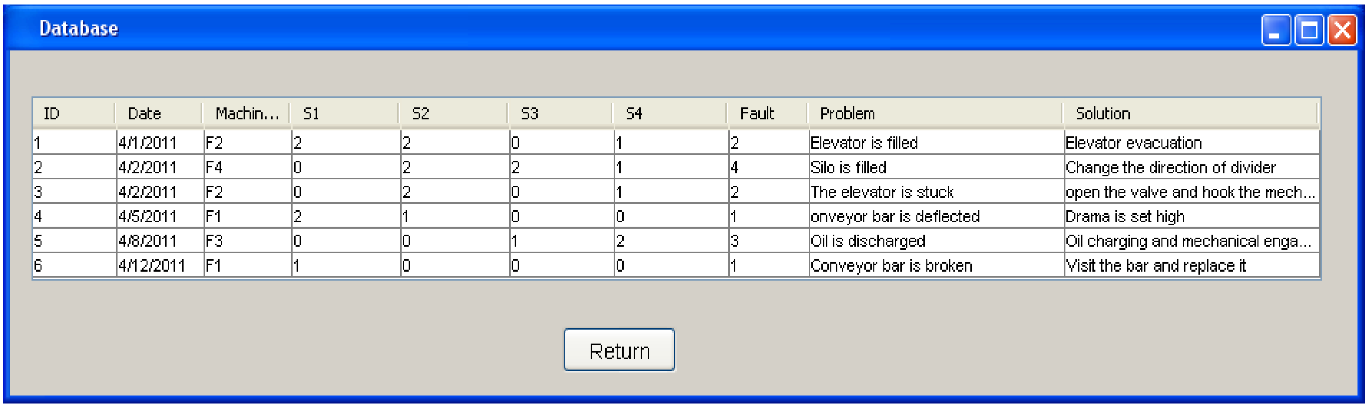


Fig. 3: Case retrieval-frontpage



ID	Date	Machine ID	S1	S2	S3	S4	Fault	Problems	Fualt Sources	Similarity
4	4/5/2011	F1	2	1	0	0	1	conveyor bar is deflected	Drama is set high	0.7
3	4/2/2011	F2	0	2	0	1	2	The elevator is stuck	open the valve and hook the mechanical er...	0.6
5	4/8/2011	F3	0	0	1	2	3	Oil is discharged	Oil charging and mechanical engagement	0.55

Fig. 4: CBR diagnostic results



ID	Date	Machin...	S1	S2	S3	S4	Fault	Problem	Solution
1	4/1/2011	F2	2	2	0	1	2	Elevator is filled	Elevator evacuation
2	4/2/2011	F4	0	2	2	1	4	Silo is filled	Change the direction of divider
3	4/2/2011	F2	0	2	0	1	2	The elevator is stuck	open the valve and hook the mech...
4	4/5/2011	F1	2	1	0	0	1	onveyor bar is deflected	Drama is set high
5	4/8/2011	F3	0	0	1	2	3	Oil is discharged	Oil charging and mechanical enga...
6	4/12/2011	F1	1	0	0	0	1	Conveyor bar is broken	Visit the bar and replace it

Fig. 5: Case retained

3. Acknowledgements

The authors would like to voice their appreciation to the Gole Gohar Company especially maintenance team in magnetite factory who aided us in gathering necessary information.

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