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A SIMULATION-BASED EXPERT SYSTEM FOR PROCESS DIAGNOSIS

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ABSTRACT

Expert systems have been widely applied to a variety of domains including the field of intelligent industrial diagnosis. However, knowledge acquisition has been often considered as the bottleneck in expert system development. This paper describes the architecture of an expert system in industrial process diagnosis, including simulation-based knowledge generation, fuzzy knowledge representation and case-based diagnostic reasoning. In this paper, a methodology of acquiring knowledge and building up knowledge bases based on software simulation is introduced. The efficiency and accuracy of the simulation-based methodology had been verified by experimental results of performing such an expert system in a hydraulic brake system.

INTRODUCTION

Fault detection and diagnosis have been considerably interested in recent years because of the increasing requirements for automation, efficiency, reliability and safety in industrial processes. On-line monitoring and diagnosis of operational performances and conditions are important for plant safety and process maintenance profit. In reality, tasks of process diagnosis in responding abnormal events are according to the knowledge, the experience, and the mental and physical status of process operators.

Automated fault diagnosis systems can help operators to make fast and accurate decisions under abnormal conditions. Intelligent diagnostic methodologies offer solutions of technical problems by automating the diagnostic procedure and improving the performance of industrial processes. Nowadays artificial intelligence (AI) technologies have been matured enough to preserve domain knowledge in order to use the past successful experiences for decision-making in the future. Expert systems (ES) have been widely used in domains where human experts are not available or the cost of inquiring an expert is high. Applications of ES have covered fields from medical diagnosis, chemical analysis, geological exploration, computer configuration, plant operation, marine navigation, to real-time process diagnosis and control [Liao 2005].

However, the knowledge acquisition problem has been commonly considered as a major bottleneck in the development of expert systems [Wu 2003] although a wide variety of ES has been built. In many industrial systems, the knowledge is not available for the synthesis of a diagnosis system. All diagnosis methods assume firstly the existence of particular knowledge for instance the existence of a numerical database corresponding to the various operating modes of the process, or the existence of experts able to verbalize their experience of a given process, etc. [Toscano 2002].

Practically, four knowledge sources of expertise, field measurement, process simulation, and enterprise information systems (e.g. enterprise resource planning (ERP) and manufacturing execution system (MES) [Tao 2004]) enable the performance of the knowledge acquisition for an ES in industrial fields. However, even the best domain specialists do not have complete experience for building efficient knowledge bases since the complexity of industrial processes; measuring data and gathering operational knowledge from industrial application fields and enterprise information systems will probably take several years before sufficient knowledge is collected; and some operational conditions are never allowed to actually appear in field measurement. To reduce the required development time and effort for an ES, it is possible to build up the knowledge base with knowledge generated by software model and its simulation.

This paper presents a simulation-based diagnostic ES for industrial processes. One purpose of this research is to investigate the possibilities of using industrial simulation to generate desired knowledge for intelligent diagnostic reasoning. After a brief overview of the introduced diagnostic ES in this paper, three stages, the simulation-based knowledge generation, the fuzzy knowledge representation and the case-based diagnostic reasoning, of building such an ES are introduced. The simulation-based ES had been validated by experimental results.

OVERVIEW OF THE DIAGNOSITC EXPERT SYSTEM

ES, as a branch of AI, has been developed in last decades. The basic idea of ES is that the expertise may be transferred from human specialists to computer. The knowledge, or the expertise, is stored in computer and then is retrieved for specific advices or solutions when needed based on the inference of computer. In this situation, an ES acts as a consultant which gives advices and explanations and potential logic. Thus applications of

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ES are critical in decision-making and problem solving in fields of industry process monitoring, detection and diagnosis.

In the diagnostic ES introduced in this paper, the processing and analyzing of information are automated to fully explore the possibilities of anticipatory control and predictive maintenance. Knowledge of operational conditions, operational actions and maintenance strategies can be built up in a database system – the knowledge base. The monitored operational condition can then be assessed by algorithms combined with the built knowledge bases, and the proper operational actions can be recommended or automatically carried out. The basic concept of the ES is shown in Figure 1.

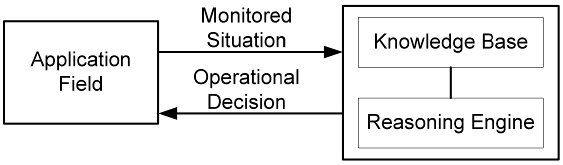

Figure 1. Basic concept of the diagnostic ES

The application field supplies facts or other information to the ES and receives expert advice or expertise in response. Internally, the ES consists of two main components. The knowledge base contains the knowledge with which the reasoning engine draws conclusion. These conclusions are ES's responses to the application field queries for expertise [Giarratano 1998].

The structure of the introduced diagnostic ES in this paper is shown in Figure 2.

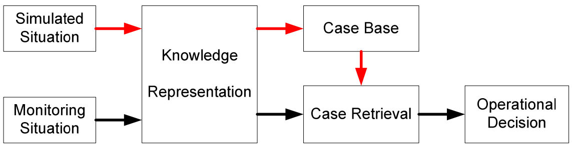

Figure 2. Structure of the diagnostic ES

This system is constructed in three stages.

In the knowledge generation stage, the knowledge of supporting process diagnosis is derived from simulation. Process model simulates and explores the effects of process operational conditions. Quantitative and qualitative forms of knowledge are abstracted from results of simulation. Generated knowledge can be readily represented and stored into underlying knowledge base to support diagnosis reasoning.

In the knowledge representation stage, the knowledge derived from simulation are represented as cases with ES recognizable forms and stored into knowledge base. This stage is accomplished by fuzzy knowledge representation algorithms.

The diagnostic reasoning stage invokes the case-based reasoning mechanism. Cases derived from simulation contain the simulated process situation description, its relevant process discovery and known solution. For newly monitored process situations, the process discovery and the solution are those desired knowledge which will be retrieved by an non-modeled associative case completion algorithms in this stage.

KNOWLEDGE GENERATION

Classical fault detection and diagnosis methods based on limit value checking of some important measurable parameters do not simulate deep process activity. One of the advantages of modeling techniques that comes from classical numerical fault detection methods is the possibility of detecting developing faults at an early stage (fault prediction). [Angeli 2001]. Nowadays the attempt to model-based diagnostics and control of industrial processes is well-known [Korbicz et al, 2004]. Many such industrial applications are reported where complex industrial installations consisting of numerous pieces of equipment and other hardware, controlled in the open loop by human operators who apply their own knowledge and skill acquired during long-term activities [Moczulski 2004].

In order to build up desired knowledge base through the simulation of industrial process, a process model will be developed and implemented. The resulting software model is used to generate knowledge for the diagnostic ES.

To reach the generation of knowledge, the software model is able to simulate accurately enough the real system in both healthy operational conditions and failure modes. The objectives for the development of the model are to gather knowledge about the behavior of the real system during both normal operation and operation after the introduction of failures, and to collect the gathered knowledge in a database that can be used by the linked ES to determine the occurring failures in the real system.

For simulation and the comparison of important parametric values from a simulated system and the corresponding measured values form the system performance, there are some requirements for the overall structure and functional design of the model. Firstly the model should be based on process physics and contain sufficient adjustable parameters to enable matching between measured and simulated results; secondly the model should be dynamic since most process activities under continuously changing operating conditions; thirdly the model should have standardized input and output parameters and supply measurable parameters for inputs and outputs; fourthly the model should be modular because the process is possible to replace and add components.

KNOWLEDGE REPRESENTATION

The specific output of the simulation and the original output of field measurement are not suitable to further reasoning process of a diagnostic ES. The task of knowledge representation stage is to represent simulated and monitored operational conditions as cases which can be used for intelligent reasoning.

Due to the abundance, complexity and uncertainty of industrial knowledge, knowledge representation is an especially difficult and time-consuming task. Most

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knowledge sources or actual instances in real-world applications contain fuzzy or ambiguous information. Expressions of the domain knowledge using fuzzy descriptions are thus seen more and more frequently. For many knowledge-intensive applications, it is important to develop an environment that permits flexible modeling and fuzzy querying of complex data and knowledge including uncertainty. [Koyuncu, et al, 2005]. In industry, it is hard and unnecessary to give exact definitions or descriptions of industrial concepts and relationships among concepts. As what a process operator does, it is also not necessary to use precise information for understanding industrial events. To express vagueness and imprecision of industrial events and their relationships the theory of fuzzy logic is employed in knowledge representation.

To overcome limitations of traditional way to acquire knowledge from a industrial process, the knowledge representation stage is based on aims of identifying the operational situations of the process from the data, then creating situation description to describe events of process, and finally, integrating this knowledge in the knowledge base (the case base). Three steps and three concepts are involved in this stage:

The data-handling step: The historical database covers representative periods. Data from each time period were considered as a particular data set. Great influences exist in the data set such like abnormal values, missing values or strange values. A statistical analysis was carried out to filter some signals and to remove the redundancy of the database. Then the final database was then structured in the format which contained the time period in rows and the variables in columns.

The classification step and concepts of attribute and event: Once the historical database was structured in a rows and columns format, it was fed to a clustering tool in order to conduct the classification step. Each cluster should represent a group of variances within a certain time period characterized by a particular situation of the process. Figure 3 shows examples of such a clustering which are able to represent most of possible variance patterns of industrial events.

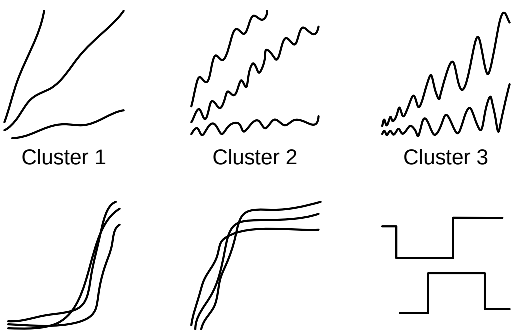

Figure 3. Clustering of industrial events

Variance quantity (A_q), variance pattern (A_p) and variance response level (A_r) are three fuzzified attributes for describing any industrial variance. For any monitored parameter, A_q represents the quantification of the variance which could be high, middle or low; A_p represents the pattern of the trend of the variance which could be smooth in/decrease, vibrated in/decrease or fly-up/down, or jump up/down; and A_r represents the intensity of the variance which could be acute/dull, fast/slow, or medium. Attributes represent how a parameter varies.

An event is defined as the combination of three attributes belongs to the event its own. An event (E) is a triple representing knowledge. It consists of three attributes which denote details of the variance of the event. An event can be represented:

$$E_n\,(A_{qn}, A_{pn}, A_{rn})$$

The case representation step and the concept of process situation description: The decision-making of the ES is performed by case-based reasoning. Cases stored in case base are considered as old cases and named as completed cases. Since the initial setting of simulation condition is known and the knowledge of simulated condition is derived from simulation, the content of a complete case is made up of the process situation description, known operational discoveries and its relevant solutions. In contrast, newly monitored operational situation is considered as new case and represented as incomplete case which contains only the process situation description. A situation description (S) is a description of a specific operational condition. Any situation can be described by the combination of its relative events:

$$S_m\,(E_{m1}, E_{m2}, \ldots, E_{mn})$$

Situation description provides the information of how current situation related parameters vary. Situation description is the main part of case representation. With adding the known discovery and solution which had been preset during simulation, a complete case is represented as:

$$Case_m : S_m\,(E_{m1}, E_{m2}, \ldots, E_{mn}, Discovery, Solution)$$

DIAGNOSITC REASONING

The main task of diagnostic reasoning is to retrieve operational discoveries and solutions from old cases stored in case base when a new incomplete case comes.

Instead of rule-based reasoning and other inference technologies in traditional ES applications, the case completion process uses an algorithm of non-modeled association which is a type of content-addressable memory (CAM). It includes common technique such as hash table for speeding-up the knowledge retrieval process. The idea of associative memory device was originally introduced by Vannevar Bush in 1945 [Bush 1945] which is a technique of using association memory to overcome the computational complexity and the complexity of knowledge management. The non-modeled association utilizes an associative lookup as opposed to an indexed lookup. Associative lookup is inherently very flexible based on the ability to perform similarity and proximity based lookup as opposed to the more brittle and explicit characteristics of index-based lookup because it can be understood as co-occurrence inference which avoids the complexity of modeling and knowledge retrieval. The principle of non-modeled associative case completion is shown in Figure 4.

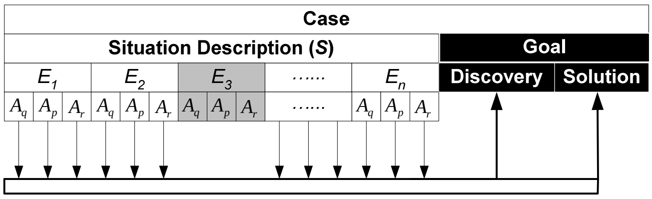

Figure 4. Principle of associative case completion

In Figure 4, attributes in white color present in both complete and incomplete cases; attributes in gray color present only in complete case but not in incomplete case; goal fields denote the missing knowledge which new case is looking for. Only the attributes present in the incomplete case are used in associative computation. Results are determined based on the frequency of the co-occurrence of attributes within the goal field. The association algorithm completes some partial or incomplete information into a recognizable condition. It is applied by evaluating the similarity between new and past operational situations and then to retrieve the lacked knowledge of incomplete cases such like operational discoveries and maintenance solutions from past complete case. Case completion algorithm is also one solution of the missing-value problem of field measurement.

SYSTEM PERFORMANCE AND EXPERIMENTAL RESULTS

The diagnostic ES and its software model are validated against field measurements. Validation involves the evaluation of the output accurateness, the system stabilities and statistical analysis based on theoretical process knowledge. A test facility of hydraulic brake system had been applied for evaluating the model, the simulation and the ES.

The Test Facility

The analyzed brake system consists of three components: a hydraulic disc brake, a belonging hydraulic power unit and a controller. The controller monitors the speed of the brake disc and depending on this speed, it controls the amount of oil the hydraulic power unit supplies to the brake. This delivered amount of oil determines the braking force with which the brake is applied to the brake disc and as a result the deceleration of the brake disc.

The facility of field test is shown in Figure 5. The motor has a nominal speed of 1500rpm and drives the low speed shaft through a poly-V-belt transmission with a ratio of (3.21:1). Normally the low speed shaft goes into a gearbox where the speed is increased and transmitted to the high speed shaft.

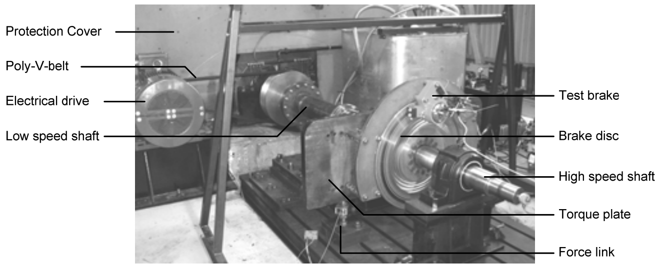

Figure 5. The test facility of hydraulic brake system

The Simulink Model

A dynamic model of the hydraulic brake system as it functions within the test facility has been developed and implemented. The mathematical software model has been built in software package Simulink. The model is able to generate simulated operational data and to gather information about the process values that are the indicators for the most important failure causes of the hydraulic brake system. Simulation results are sent to the ES and represented as complete cases stored into knowledge base.

Four main parts of the brake system, the hydraulic disc brake, hydraulic power unit, the controller and the brake disc, are included in the model. For the aim of modularity of the model, which results in a better overview and maintainability of the software model, the four physical parts of the system each forms a separate subsystem. The relations of subsystems and their causalities had been known before the systems were modeled. Four parts of the system and their relative parameters are shown in Figure 6.

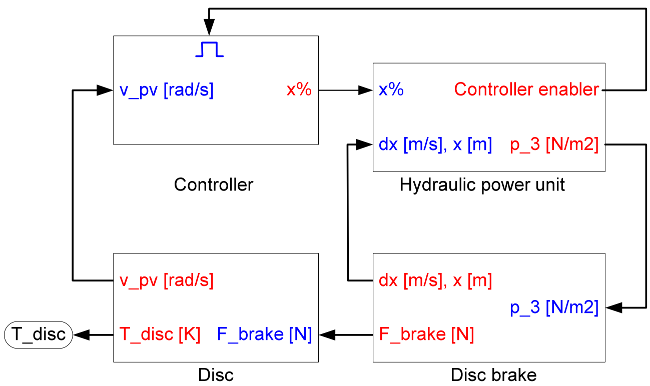

Figure 6. The Simulink model

Where

v_pv is the velocity of brake disc;

$x\%$ is the pulse width modulation of controller;

x is the displacement of the brake pad;

dx is the velocity of the brake pad;

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$p3$ is the pressure in brake cylinder;

F_brake is the braking force;

T_max_disc is the temperature of the brake disc.

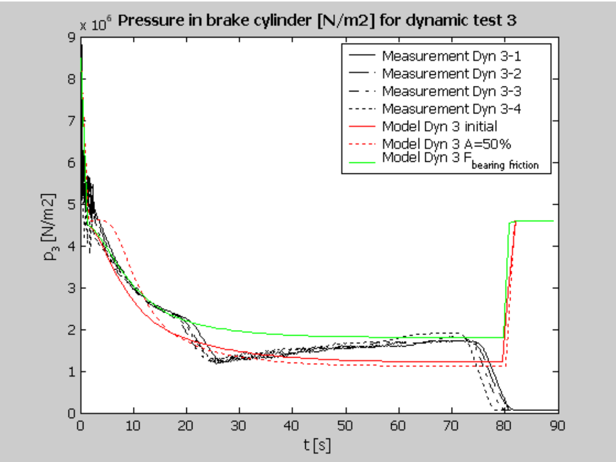

Figure 7. Example of model matching

Verification is the initial evaluation of the model mainly based on theoretical process knowledge. Verification should show the ability of the model to describe the physical process. Matching is understood to be the adjustment of parameters in the model, such that the simulated outputs approximate the measured data as accurately as possible over the entire operational range. To reach the purpose of model verification and matching, steady state tests and dynamic tests had been executed. Figure 7 shows an example of results from one of dynamic tests.

Actually the verification and matching of the model had been quite easily done since the trends of process values generated by the model corresponded quite well with the trends in the measured data from test facility.

User Interface

The ES gives output with the code of newly monitored situation, the code of retrieved situation, the indication of possible system failure mode and relative operation solution, and the confidence level of case retrieval. The situation code is the simplified process situation description. It is sequentially listed attribute representations of all relevant events. Indication of retrieved solution originally comes from its simulation initial setting. The confidence level denotes how similar two cases are. Figure 8 shows an example of the output of the ES when the failure mode of grease on brake disc occurs.

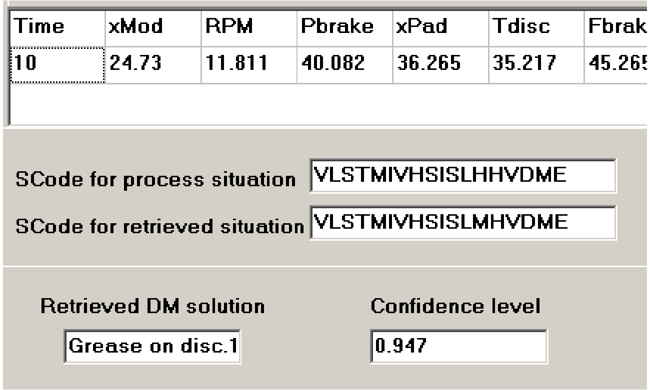

Figure 8. User interface of the ES

Results

The simulation-based ES had been tests by effects of failure modes in the hydraulic brake system on the behaviors of both the simulated and measured process values. For the current software model seventeen failure modes that can be both simulated and measured from test field are most interested.

The ES can be evaluated based on the output it gives. During field tests, the operational condition of the measured data offered to the ES is known, which means that the failure mode is known. Therefore, it is easy to verify if the retrieved process discovery and decision-making solution given as output by the ES corresponds with the failure mode as measured. Figure 9 shows the evaluation results of the ES during the blocks of ten seconds braking time, offering the measurement during failure mode of "control pressure low".

From experimental results it can be concluded that the simulation-based diagnostic ES gives correct enough maintenance decisions.

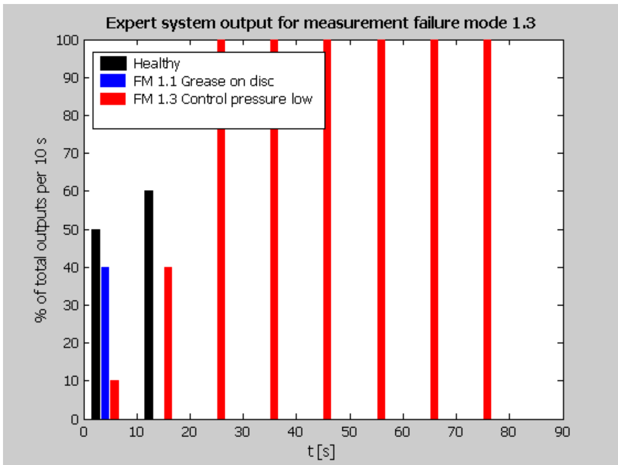

Figure 9. Evaluation of ES output

CONCLUSIONS

It is becoming increasingly clear that knowledge systems are playing a major role in the modern industrial process diagnosis. One unique aspect of the introduce diagnostic ES is that the solution of bottleneck problem of

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knowledge acquisition during developing an ES is achieved by the use of simulation in discovering failure causalities and possible operational solution in industrial processes. The methodology of simulation-based knowledge generation shows its efficiency and accuracy of building up knowledge base for an intelligent system. Fuzzy knowledge representation enables system to easily represent outputs of simulation for diagnostic reasoning. Based on results of experimental implementation, it is concluded that the simulation-based diagnostic ES provides accurate enough outputs for process diagnosis and decision-making.

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