Distributed Intelligent Fault Diagnosis for Hydraulic Motors

Zhijun Rong, Kuisheng Chen, and Baosheng Ying

Wuhan University of Science and Technology, 947
Heping Road, China 430081

rongzhijun@263.net

Abstract

Information technology and artificial intelligence technology hold great potential for enabling the distributed and intelligent fault diagnosis. Hydraulic motor is a common actuator having a high impact on the system performance. There has been significant work on fault detection and diagnosis for hydraulic motors. This paper presents a multi-agent framework for hydraulic motor fault diagnosis based on three-tier architecture that can support a distributed application. Six types of agents implemented by computers are investigated. In particular, the communications between agents are described. It can provide a handy trouble-shooting tool that cuts down the time involved in diagnosing failures in hydraulic components in general, and in motors, in particular.

Keyword: Hydraulic motor; Fault diagnosis; Multi-agent; Three-tier.

I. Introduction

Hydraulic motor is an actuator that converts the hydraulic energy of a pressurized fluid into mechanical energy of a continuous rotation. It is widely applied in the machinery for construction, mining, shipping and metallurgical industries, etc. It has a high impact on the efficiency and reliability of hydraulic system. The hydraulic motors are known to exhibit a sensitive dynamic behavior that is highly influenced by many factors. The dramatically different dynamic behavior can be used for the prediction of faults. Fault diagnosis for hydraulic motors relied on human intervention to recognize small problems such as vibration and noise, and personal experience to obtain solution in the past days. With the rapid development of high technologies in the world, the industrial equipments become more and more complicated and sophisticated. Fault diagnosis for industrial equipments is facing serious problem due to distributed and collaborative industrial activities. In hydraulic applications there is a growing trend toward information technology and artificial intelligence technology [1-3]. These approaches developed for fault diagnosis of hydraulic system can be grouped as [4-8]: expert systems; qualitative reasoning; model-based diagnosis from an artificial intelligence perspective; model-based diagnosis based on control engineering techniques; neural networks; web-based; distributed artificial intelligence such as multi-agent. As we know, fluid power systems present two main challenges to establish fault diagnosis architectures. Firstly, the systems tend to be very nonlinear. Secondly, behavior is frequently dynamic, meaning that the output of the system is a function of time as well as any inputs to the system [3]. In expert systems in presence of nonlinearities, the number and complexity of rules required by the diagnosis increase.

Similarly nonlinearities increase the size of search space and result in slower and less reliable diagnosis for qualitative reasoning approaches. Model-based approaches typically rely on linear models. Therefore increasing system nonlinearity leads to larger modeling errors and less accurate diagnosis. Neural networks model can be used for identifying faults in hydraulic components. But for practical application, the basic NN algorithm has two disadvantages. One is the low speed of training; the other is their tendency towards local minima. There is no perfect approach for fault diagnosis of hydraulic components as only one technology is applied. Neural networks based on genetic algorithm provide a proper approach for fault diagnosis and is relatively successful. Now cooperative analysis and diagnosis should be done on the web in a distributed application. Multi-agent technology [9-13] as a branch of distributed artificial intelligence shows some promises for distributed and intelligent diagnosis.

In this study, we attempt to establish a multi-agent framework for diagnosis of hydraulic motor, identify the relation between agents and introduce the application of multi-agent technology for hydraulic motor fault diagnosis. The remainder of this paper is organized as follows. In Section 2, the diagnosis strategy and fault characteristics of hydraulic motor are described. In Section 3, a multi-agent framework for fault diagnosis is given and function of each agent is investigated. In Section 4, a fault diagnosis process is proposed as case study based on the framework. Finally, in Section 5, the work is summarized and some future directions are highlighted.

II. Diagnostic Strategies

Fault diagnosis provides a systematic view of the hydraulic motor to identify failures and the causes and effects of such failures. There are many approaches to diagnose the hydraulic motor faults like vibration diagnosis, model identification, statistical diagnosis, fuzzy diagnosis, etc. Many traditional approaches to fault diagnosis are based on signal processing techniques including three main steps: the first consists in measuring signal, the second in refining symptom; the third in detecting and identifying fault. The status data of hydraulic motor can be grouped into two categories: one is energy data like vibration, noise, temperature, etc; the other is physical state data like leaked oil, rust, crack, etc. Symptom can be extracted from these data. The drawbacks of traditional methods are as follows: experience and knowledge of domain experts cannot be utilized completely; using forward inference only leads to poor new information; have no self-learning ability; the diagnosis results without explanation; diagnosis program is too rigid to be modified and extended; geographically distributed people cannot analyze and diagnose cooperatively. Therefore, a new approach combining operational research and intelligent decision-making process is needed and a web-based realization can be considered as being an essential requirement. The diagnostic strategies meeting new requirement are shown in Fig.1.

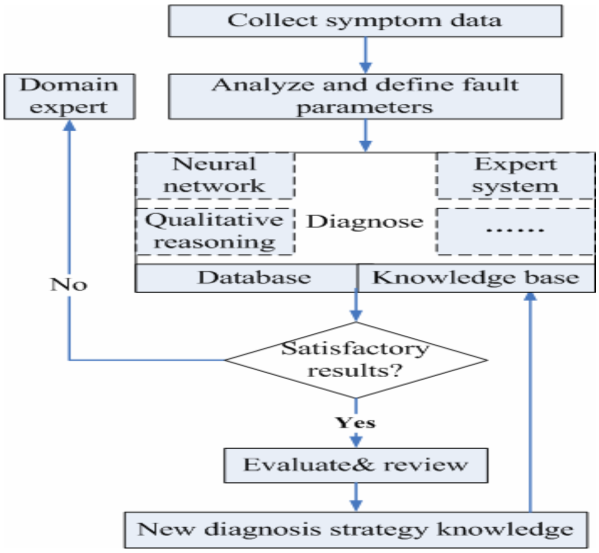

Fig. 1. The diagnostic strategies

The status data are received from the hydraulic motor in real time or offline. These data are sent to working memory of intelligent fault diagnostic model and represented in required format. The intelligent diagnostic model loads the data from working memory and makes a diagnosis. If the diagnostic model cannot give solution the alarm message will be sent out for requesting help of domain experts. If the results are reliable and validated by experiments, the diagnosis process will be evaluated and the strategies knowledge will be extracted. New understanding or new information about the diagnosis process well be stored into knowledge base and database. The relationships between symptoms and faults are described as follows: symptom set consisting of all symptoms related to fault; symptom set consisting of some symptoms related to fault; symptom set consisting of fuzzy symptom related to fault. Three diagnosis strategies for these three conditions can be investigated: sequential, combinational and fuzzy fault diagnosis. Sequential fault diagnosis takes a global view to track down the causes of the problem accurately. Combinational fault diagnosis gives relating probability of cause and result on the basis of statistics. Fuzzy fault diagnosis gives the degree of membership of fault cause by dealing with fuzzy symptom data. Fuzzy data occurs when operators need to express the symptoms in an approximate way by verbal judgement or by stating a single number taken from the 1-9 comparison scale. In fuzzy logic, the truth of any statement is a matter of degree. If we have a particular criterion A, we can associate, with each value in X, a number $A[X_i]$ in the interval [0,1], indicative of how well X_i satisfies criterion A, which of course then specifies A as a fuzzy set of X. We can define $A[X_i]$ is the degree of membership [9]. The symptoms are always described by fuzzy information like high noise, serious leakage and vibration, etc. The degree of noise, leakage and vibration can be indicated by $A[X_i]$ instead of by semantic description like “high” or “serious”. According to the diagnostic strategies, artificial intelligence technologies, such as expert systems, fuzzy logic and neural network are necessary to support the hydraulic motor fault diagnosis.

III. Multi-agent Framework for Distributed Fault Diagnosis

Agent is a basic term of distributed artificial intelligence and can be treated as an extended object-oriented program. Each agent has its own control thread and runs independently of each other. Agents exchange messages with each other while performing their roles. They can determine the way of dealing with messages by themselves. Agents continuously test and change their strategy in dependence on their interactions and the current situations. The multi-agent framework for distributed fault diagnosis is illustrated in Fig.2. It has six different types of agents: protocol agent (PA), initial diagnosis agent (IDA), motor information agent (MIA), making-decision agent (MDA), evaluation &review agent (ERA), database&knowledge base agent (DKA). The framework presented in this paper is developed using the three-tier architecture model in which the client tier, application tier and database tier are developed and maintained as independent modules. The agents perform their tasks in this three-tier architecture. PA works in client tier, other agents except DKA will run in the application tier, and DKA will work in database tier. PA defines the bottom tier protocol such as HTTP, FTP, etc for interaction with user front, accepts the application request from user protocol agent on specific port and transmits the request to IDA. It implements service request routing function, sends the application request to IDA according to types of service interfaces announced by itself. MIA is responsible for managing the motor information including the maintenance schedule, repair history, location, service life and working condition, etc. This agent can provide two significant benefits. Firstly, the diagnosis process has direct relation with certain fault object and the diagnosis result can be tracked to the original cause even it has been refined to be knowledge rule. Secondly, the diagnostic time can be shortened because MIA will ask DKA to provide the old diagnostic record directly if the symptoms are same. DKA identifies type, location and potential performance of database. It can apply CRUD (Create, Retrieve, Update, Delete) operation to database, provides support for sharing the database on different sites, saves costs and improves the data source efficiency. It is responsible for fetching all the required data and available diagnosis knowledge strategies for IDA, MDA and ERA. In addition, DKA refines the evaluation results from ERA and extracts knowledge from them. Due to the nature of DKA, connectivity to any existing data storing and knowledge management mechanism can be easily established and maintained. IDA handles incoming data and represents the knowledge. It manipulates the fault diagnosis with the help of embedded expert system or neural network model. The training data for NN model and knowledge rules for expert system are provided by DKA. If it failed, the IDA will announce the fault cannot be identified and no solution can be given. Thereafter, domain experts are needed. If it accomplishes the task, the diagnostic results will be sent to MDA. MDA is the core of the framework. The results from IDA are on the basis of superficial diagnosis data that is a bit fuzzy and subjective. MDA takes into account the previously unknown information and unexpected relationship in data. It gives the final solution and the final results will be sent to ERA. ERA is responsible for examining the work and making the judgments. The diagnostic strategies and process will be summarized and the conclusion will be sent to DKA as the source of database and knowledge base.

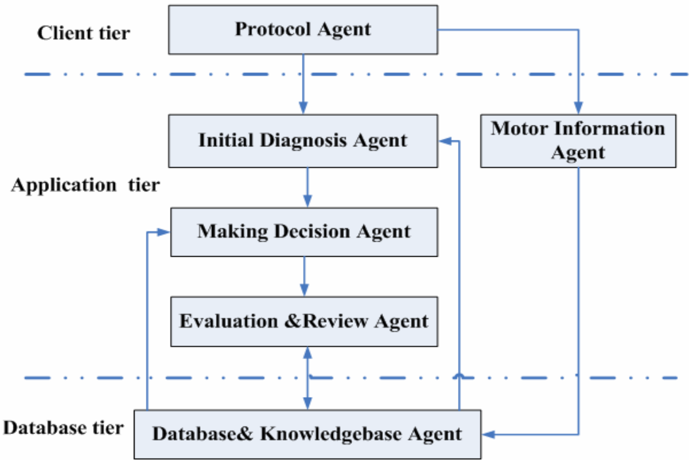

Fig. 2. Multi-agent framework for fault diagnosis of hydraulic motor

IV. Case Study

Too low speed is one of the common faults of hydraulic motor. Wearing, choking, viscosity and oil level have direct connection to the speed. In fluid power industry, it is necessary to identify and locate fault causes while the fault effects are always known for the poor operation performance.

When an operator observes the fault, he/she tries to find the causes with his/her own experience or turning to external help such as domain experts and fault diagnosis system. Domain experts are always not available at any time because they are not everywhere at disposal and are limited in their number. The distributed and intelligent fault diagnosis can ease this problem by exchanging and utilizing expert knowledge with the computer on the web. The following case study illustrates the diagnosis process as shown in Fig.3. The first phase of the diagnosis process begins at a new fault arrival. New requests are handled by the PA, which collects input from operators and prepares all data required by other agents before they initialize and execute the fault diagnosis mechanism. Data collection is realized through PA that comprised two parts: one dedicated to the collection of fault symptom data and the other dedicated to the collection of hydraulic motor specific information. When an operator enters the system, he/she declares the fault results like slow working speed, etc. Furthermore, the operator inputs the specific information like the service life, working condition and past solved problems, etc. The system will ask the operator to provide the diagnosis parameters like oil level and viscosity, etc. The operator should try his/her best to meet the requirement because that will affect the accuracy of fault diagnosis. Some symptom data can be expressed in value such as viscosity and oil level; while some symptom data can be expressed in fuzzy semantic format such as wearing and leakage. The symptom data provided by operators will be sent to IDA as input of intelligent inference and computing. KDA will provide the history diagnosis results and potential fault data for IDA according to the motor specific information. IDA computes and sends the computing results with degree of belief of each fault cause to MDA. If IDA cannot perform the tasks, domain experts will be asked to give solution and the results will be sent to ERA combined with IDA failure results. MDA is a kind of decision support system that recommends solution and shows potential causes and effects [13]. Potential fault will also be analyzed. The results from MDA will be applied into practical operation and the application results will be input to ERA. ERA checks diagnosis process and refines new diagnosis strategies knowledge. These new knowledge will be used to update the database and knowledge base by DKA. Therefore, the self-learning ability will be improved. From this case, each agent is a set of program that has its own task and communicates with other agents its own intention. It can respond requests from other agents autonomously.

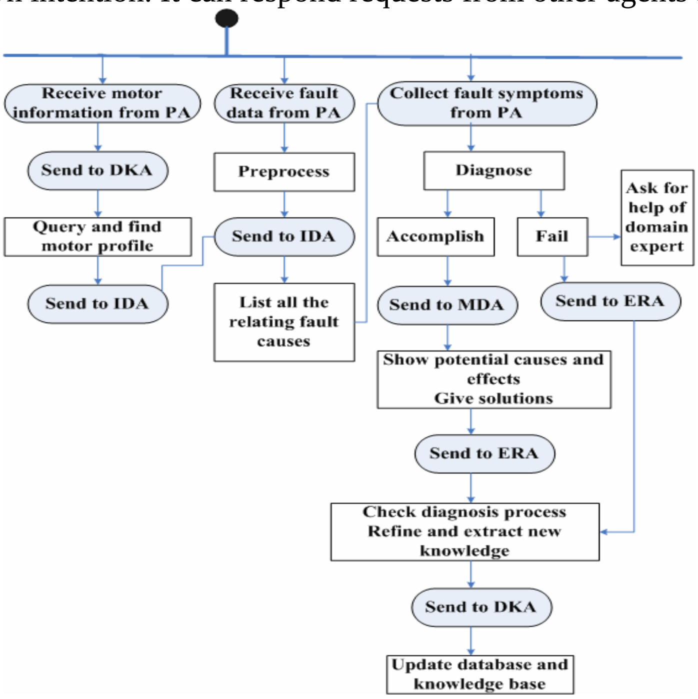

Fig. 3. The activity diagram of diagnosis process

V. Conclusions

The research work described in this paper demonstrates that development of multi-agent techniques for the fault diagnosis of hydraulic components is now within the realms of possibility. More specifically, the process of fault diagnosis is thoroughly described and focus is given on the developed methodologies, which are specified keeping in mind the effort for establishing efficient, quick and easy fault diagnosis. The presented multi-agent framework deploys techniques for intelligent and distributed fault diagnosis. The functional architecture is described in detail, and all types of participating agents analyzed in terms of their functional specifications. Though it is possible to follow more than a single approach, a multi-agent technology, is able to suggest the most suitable fault diagnosis method, which is then supported by the tools of fuzzy sets, expert system, neural networks and distributed application. The integration of intelligent computing and multi-criteria decision support methods is discussed in this research, and work to date indicates that it is likely to be a usable and promising methodology in fault diagnosis. It is important to address the future research effort to complete the development of the system and to study communications between agents. As the presented multi-agent framework can be extended to fulfill the needs of a distributed network, introducing mobility characteristics to the existing agent types and enlarging the knowledge base is the main task.

References

[1] David L. Waltz, “Artificial intelligence: realizing the ultimate promises of computing”, http://www.cs.washington.edu/homes/lazowska/cra/ai.html.

[2] Mohammed E. Haque, K.V.Sudhakar, “ANN back-propagation prediction model for fracture toughness in microalloy steel”, International Journal of Fatigue, vol.24, 2002, pp. 1003-1010.

[3] Crowther WJ, Edge KA, Burrows CR, Atkinson RM & Woollons DJ. “Fault diagnosis of a hydraulic actuator circuit using neural networks - an output vector space classification approach”. Proc IMechE, Part I, vol 212, 1998, pp. 57-68.

[4] Hogan PH, Burrows CR & Edge KA. “Development of a knowledge-based system for the diagnosis of faults in hydraulic systems”. A.S.M.E Winter Annual Meeting. Dallas, Texas, 1990.

[5] Edge KA, Boston OP, Burrows CR, Darling J, Woollons DJ, Atkinson RM & Hawkins PG. “An approach to automated fault diagnosis of hydraulic circuits”. ASME IMECE, San Francisco, Cal, USA, 12-17 November, 1995.

[6] Wang L-M, Burrows CR, Edge KA & Chapple PJ. “A software package for on-line performance monitoring and fault diagnosis of hydraulic circuits”. Seminar on Maintainability and Reliability of Hydraulic Systems. I.Mech.E., London. 1 May, 1991.

[7] Atkinson RM, Montakhab MR, Woollons DJ, Hogan PA, Burrows CR & Edge KA. “DESHC: A diagnostic expert system for hydraulic circuits”. CERT-ONERA International Conference on Fault Diagnosis, Toulouse, France, April 1993.

[8] Atkinson, RM, Woollons, DJ, Crowther, WJ, Burrows, CR & Edge, KA.“A neural network approach to fault diagnosis in electro hydraulic systems”. Proc. COMADEM ‘96, Sheffield, UK.

[9] F. T.S. Chan, B. Jiang, N. K.H.Tang, “The development of intelligent decision support to aid the design of flexible manufacturing systems”, Int .J. Production Economics, vol 65, 2000, pp. 73-84.

[10] A. L. Symeonidis, D. D. Kehagias, P. A. Mitkas, “Intelligent policy recommendations on enterprise resource planning by the use of agent technology and data mining techniques”, Expert system with applications, vol 25, 2003, pp. 589-602.

[11] K. Shaalana, M. ElBadryb, A. Rafea, “A multiagent approach for diagnostic expert systems via the internet”, Expert Systems with Applications, vol 27, 2004, pp. 1–10.

[12] S. Parka, V. Sugumaran, "Designing multi-agent systems: a framework and application", Expert Systems with Applications, vol 10, 2004, pp 1–13.
[13] S. K. Ong, N. An and A. Y. C. Nee, "Web-Based Fault Diagnostic and Learning System", Int J Adv Manuf Technol, vol 18, 2001, pp. 502–511.

Zhijun Rong is an assistant professor at the Department of Industrial Engineering, Wuhan University of Science and Technology, PR. China. She received her bachelor (1996), master(1999) degrees from Wuhan University of Technology, PR. China. Her current research interests include collaborative design, computer integrated manufacturing system, and intelligent fault diagnosis. She has published one book and more than 10 research papers in scientific journals and international conferences.

Kuisheng Chen has been on the Wuhan University of Science and Technology faculty since 1980. He is now a full professor and the dean of the School of Mechanical Science and Engineering, WUST. Prof. Chen is also the founding director of WUST's fluid power laboratory. Prof. Chen 's research interests include electrohydraulic systems, hydraulic components and artificial intelligence applied to hydraulic systems. He has published three books and more than 60 papers in scientific journals and international conferences.

Baosheng Ying is a professor at the Department of Industrial Engineering, Wuhan University of Science and Technology, PR China. He obtained his bachelor (1986), master (1988) and PhD(1991) degrees from Huazhong University of Science and Technology, PR.China. Dr. Ying has been working on contemporary integrated manufacturing, networked design and manufacturing for more than 15 years. He has published more than 30 research papers in scientific journals and international conferences.