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Diagnostics of Rotating Machinery using Recursive Bayesian Estimation

재귀 베이시안 추정을 이용한 회전기기 진단

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Abstract

Since power plant is an important system to provide electricity, it is necessary to monitor it in order to operate safely. Much information related with machine diagnosis exists in written form instead of digital data. So, it causes difficulties of analyzing and finding solutions. Rule-based expert system can provide flexible and effective solutions to users. In this paper, Recursive Bayesian Estimation is applied in order to increase accuracy of solutions.

Keywords: Turbine, Vibration, Pump, Bayesian Estimation, Diagnostic

I. Introduction

Power utilities and power plants operate on rotating devices such as turbines, pumps, fans and electric motors. The plant shut down due to the failure of the machines will result in significant losses and power supply failures. Therefore, it is important to regular maintenance, inspection and monitoring systems. System monitoring is undertaken through several methods and maintenance engineers, necessitating an additional monitoring system to facilitate diagnosis of the health of the device, taking into account the importance of the facility. Thus, it is necessary to develop an expert system to analyze the cause of the failure of the device and to diagnose the condition of the plant system. In order to develop the diagnostic system, it has to need abnormal conditions such as failure history, but it is difficult to accumulate digital data due to using analog gauges at real fields. So, in this paper, we intend to develop an expert system to diagnose a system of complex plant systems based on failure history literatures rather than fault state data.

II. Expert System

In the 90's, technological demands of the expert system decreased by artificial intelligence's advance but, it has been reignited by the development of the latest Text Mining. The core idea of the expert system is to deliver expertise to the computer.

Lots of information knowledge can present a flexible and effective way to solve a wide variety of problems. Expert systems can improve work efficiency by providing better solutions for inexperienced professionals and respond to situations when there is no expert. Because of these advantages, expert system is being used in various fields such as accounting, marketing, education, manufacturing, medical and especially, many studies have been conducted in the field of industrial research [1].

A. Rule-based expert system

A rule-based expert system describes the expertise as a rule. The expertise is used as an inference data to reach a reasonable conclusion. The rule-based expert system has the process of solving problems by an expert's way of thinking that can be programmed to a computer.

Based on the reference [2][3], the knowledge of the rule-based expert system was reconstructed as shown in TABLE 2. The numbers in TABLE 2 refer to extent of occurrence or probability derived from statistical data.

When user chooses machines and fault symptoms, through the knowledge base module, the system shows frequent causes and indicates how to dealing this problem. Failure symptoms and machine faults are recorded in the maintenance literature as a relation to 1 to 1. In reality, however, there are often complex symptoms when a failure occurs in a single part of the machine. Thus, it arises a problem that the user has to find out the cause of the failure of the observed complex symptoms. To solve this problem and expand the knowledge base expert system, we intend to approach through recursive Bayesian estimation.

Article Information

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TABLE 2
Causality of a Pump

Cause	No discharge flow	Insufficient capacity	Intermittent shutdown	Low discharge pressure	Short bearing life	Short mechanical seal life	Vibration & Noise	Overload
A pump cause cavitation	2	1	1	0	0	9	1	0
An aspirator tube or bell is insufficiently immersed in the fluid	1	1	1	0	0	0	1	0
Insufficient air discharge of a pump	1	0	2	0	0	0	0	0
Non condensation in liquid	0	2	3	1	0	0	0	0
The depletion of a supply tank	3	0	0	0	0	0	0	0
Foreign material of a pipe or a housing	0	9	0	7	0	0	0	0
Partial blockage of a strainer	0	3	0	0	0	0	7	0
Blockage of a pump impeller	8	8	0	0	0	0	0	5
A suction valve or a discharge valve closed	9	0	0	0	0	0	0	0
High viscosity	0	7	0	5	0	0	0	4
High specific gravity	0	0	0	0	0	0	0	2

TABLE 1
Expert System Totals by Problem Domain [1]

Classification	26
Debugging	16
Diagnosis	73
Interpretation	27
Control	10
Instruction	10
Monitoring	33
Prediction	15
Correction/repair	7
Configuration	14
Design	28
Planning	41
Scheduling	11

TABLE 3
Example of DB

Cause \ Symptom	E_1	E_2
H_1	1	5
H_2	1	2
H_3	3	1

B. Rule-based expert system using recursive Bayesian estimation

1) Identify the failure modes through Bayesian

The physical properties of the vibration factors of the fan are related to bearings, gears, etc., they don't operate independently of each other and have a complex causality. In order to figure out these associations, it is necessary to establish a stochastic model through the Bayesian network and to interpret the results.

2) Modeling for correlation analysis

To analyze correlation analysis, the structure of data and the local distribution of data should be learned. The composition and quality of the data determine to the reliability of Bayesian network.

The database is a matrix form that row and column are causes and symptoms, respectively and numbers in TABLE 3 refer to probability. The cause according to the symptom is expressed by subjective numbers based on statistical data. H is a hypothesis or a cause and E is evidence or a symptom. The probability is obtained by Eq. (1).

$$P(E|H) = 0 \tag{1}$$

The objective is a calculation about the probability of cause when various symptoms occur based on a given probability as follows in Eq. (2).

$$P(H|E_1), P(H|E_2) \rightarrow P(H|E_1E_2) \tag{2}$$

But the conditional probability of a cause for one symptom cannot be used to calculate the conditional probability of the cause for various symptoms. When various symptoms are observed, the method of estimating the cause is as follows in the Eq. (3). We can use Bayes Rule to calculate the desired probability.

$$P(H|E_1E_2) = \frac{P(E_1E_2|H)P(H)}{P(E_1E_2)} = \frac{P(E_1|H)P(E_2|H)P(H)}{P(E_1E_2)} \tag{3}$$

In the actual field, mechanical problems are manifested by a variety of symptoms, and the engineer seeks to root cause analysis. Probability combination is needed to solve root cause analysis from complex symptoms. The problem can be redefined through recursive Bayesian estimation by observing various symptoms and finding out which causes of the problem are most likely. This is a problem that is inferred when observing various symptoms, and is expressed as a Maximum Posterior Probability (MAP). We define three matrices to solve the problem.

$$A = \begin{bmatrix} P(E_1|H) & \cdots & P(E_m|H) \\ \vdots & \ddots & \vdots \\ P(E_1|H_n) & \cdots & P(E_m|H_n) \end{bmatrix} \tag{4}$$

where $\quad A_{ij} = P(E_j|H_i)$

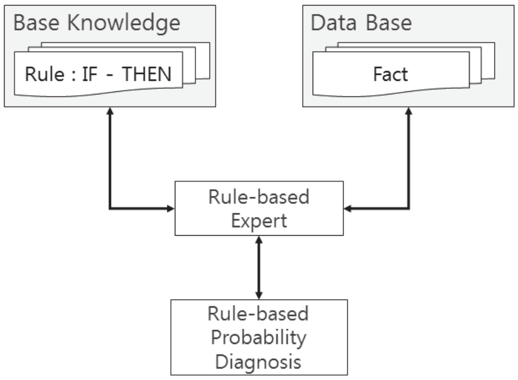

Fig. 1. Rule-based expert system.

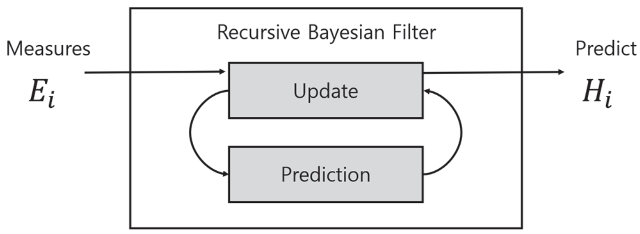

Fig. 2. Recursive Bayesian estimation.

$$h = \begin{bmatrix} P(H_1) \\ \vdots \\ P(H_n) \end{bmatrix}$$

$$J = [h_1 a_1^T \quad \cdots \quad h_n a_n^T]$$

where a_i is the ith row of A, then $J_{ij}=P(E_i H_j)$.

Therefore, when various symptoms are observed, the calculation method is as follows in Eq. (5).

$$\begin{aligned} &\operatorname{argmax} P\left(H_i \cap_{j \in Z} E_j\right) \\ &= \operatorname{argmax} P\left(E_{m_1}\middle|H_i\right) P\left(E_{m_2}\middle|H_i\right) \cdots P\left(E_{m_k}\middle|H_i\right) P(H_i) \\ &= \operatorname{argmax} P(H_i) \prod_{k \in \{n_1 \cdots n_k\}} A_{ik} \end{aligned} \tag{5}$$

Through the database, we compared to the cause reasoning values when the discharge flow rate shortage occurred (refer to TABLE 4.) and the cause reasoning values when the discharge flow rate and capacity shortage occurred.

The result of 'No discharge flow' based on Recursive Bayesian by Eq. (4) is as shown in Fig 4.

In case of 2 symptoms ocuured, an exaple is as follows. We confirmed the highest probability that the pump causes cavitation and the aspirator tube or bell is insufficiently immersed in the fluid. (refer to TABLE 5).

If the two symptoms occurred in the Rotary Pump a, the cause is shown in Fig 5.

When we combined the two probabilities, confirmed the highest probability that the aspiration tube or bell was insufficiently immersed in the fluid.

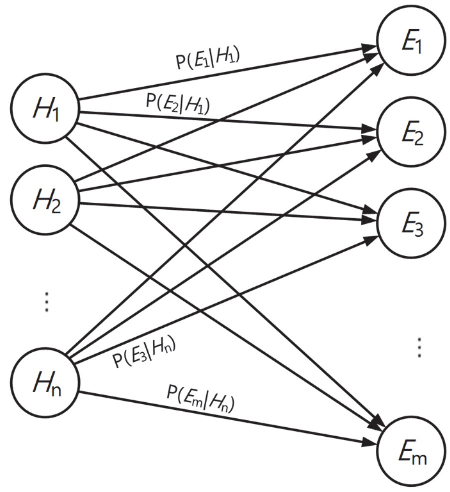

Fig. 3. Graphical representation of networks between hypothesis and evidences.

TABLE 4
Matrix of Rotary Pump for 'No Discharge Flow'

Cause	Symptom	E_1 No discharge flow
H_1	A pump cause cavitation	2
H_2	An aspirator tube or bell is insufficiently immersed in the fluid	1
H_3	Insufficient air discharge of a pump	1
H_4	Non condensation in liquid	0
H_5	The depletion of a supply tank	3
H_6	Foreign material of a pipe or a housing	0
H_7	Partial blockage of a strainer	0
H_8	Blockage of a pump impeller	8
H_9	A suction valve or a discharge valve closed	9
H_{10}	High viscosity	0
H_{11}	High specific gravity	0

TABLE 5
Matrix Rotary Pump for 'No discharge flow' and 'Insufficient capacity'

Cause / Symptom	E_1 No discharge flow	E_2 Insufficient capacity
A pump cause cavitation	2	1
A aspirator tube or bell is insufficiently immersed in the fluid	1	1
Insufficient air discharge of a pump	1	0
Non condensation in liquid	0	2
The depletion of a supply tank	3	0
Foreign material of a pipe or a housing	0	9
Partial blockage of a strainer	0	3
Blockage of a pump impeller	8	8
A suction valve or a discharge valve closed	9	0
High viscosity	0	7
High specific gravity	0	0

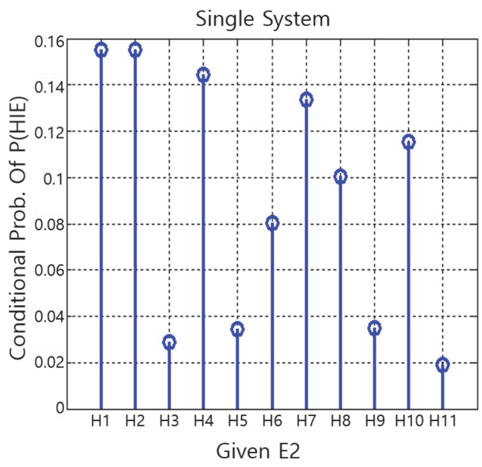

Fig. 4. Result of estimation cause of machine failure

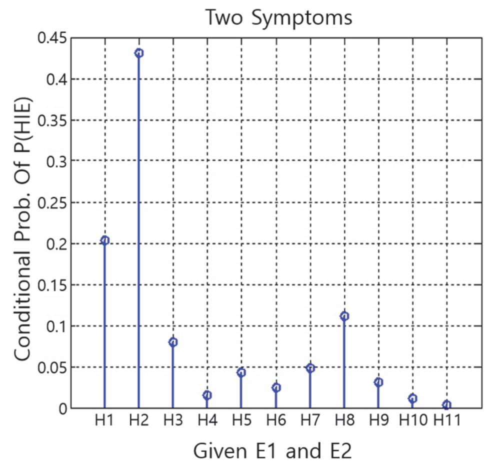

Fig. 5. Result of Recursive Bayesian estimation with multi symptom

III. Conclusion

An application for Bayesian approach for a knowledge-based maintenance decision support tool was proposed, through which extracted a machine health index and probability of root causes from multiple observed symptoms. In particular, not only a statistical approach is used but also a knowledge-based decision-making approach is used in order to analyze a non-quantifiable data set. The direction of future research can be summarized as follows: Industrial applications for Bayesian approach for a rule-based maintenance decision support are needed to demonstrate completeness and effectiveness of the proposed root cause analysis with more empirical evidence.

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