Modelling for Maintenance Using System Reliability with Degradations in Multiple Components and Their Interactions

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Abstract: This is a template for the 17th International Conference on Probabilistic Safety Assessment and Management Conference and Asian Symposium on Risk Application and Management 2024 (PSAM17&ASRAM2024)**.** The abstract for the full paper should be concise and do not exceed 2000 characters. The abstract should be written in 11 points, Times New Roman and placed before the first section with a horizontal line before and after. All text, tables, formulas, etc., presented in this paper are formatted according to the instructions below:

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1. INTRODUCTION

In Condition Based Maintenance (CBM), which has been the focus of much attention in recent years, it is important to understand the degradation state of equipment in order to develop maintenance plans based on condition monitoring data.

In the nuclear field, reliability models have been used in probabilistic risk assessment (PRA), but the reliability indices used in PRA, such as failure rates, are difficult to relate directly to the degradation state of equipment. In addition, when modeling a system consisting of multiple components, it is important to consider the dependence of degradation among the components[1]. In particular, the dependence, which has not been explicitly considered in the PRA model because it is considered to "not contribute to the risk increase of the entire system," should be considered in the model for maintenance applications.

Furthermore, in nuclear power plants, preventive maintenance is often performed before degradation reaches a detectable level, and data on the progress of degradation is scarce for some equipment. Using inference from data of other equipment by modeling degradation dependence among system components could be a solution to this lack of data.

The purpose of this study is to develop a model for estimating the state of equipment in a system consisting of multiple pieces of equipment by considering the degradation dependence among the components. This model enables inference using data from related equipment by modeling the dependence, and aims to improve the state estimation of equipment with poor degradation data.

2. METHODS

2.1. Target System

As a specific example, this study considers a system consisting of a pump and a valve connected by piping. The pump has a bearing, which increases vibration as it degrades. In addition, the motor in the pump gradually loses insulation, eventually leading to demand failure of the pump. The boundary function of the valve is maintained by the casing and gland packing. Degradation of the gland packing leads to leakage, which in turn leads to increased humidity.

The possible dependencies in this system are shown in Figure 1. In this study, degradation with a long time to failure is not considered, but only the dependency indicated by the red line in Figure 1, i.e., the relationship that vibration increases with the progress of degradation of the pump bearing, and this vibration is transmitted to the valve and accelerates the degradation of the gland packing. The degradation state of the bearing and packing cannot be observed, but the vibration and leakage can.

If leakage from the valve is detected, the system is shut down and the packing is inspected and replaced, but otherwise the presence of packing damage can only be confirmed during overhaul. Therefore, data on the state

of deterioration of the gland packing prior to its failure is scarce, making it difficult to perform maintenance at the appropriate time when the packing is likely to fail.
Considering the dependence here, it is thought that more detailed estimation of packing deterioration can be achieved by utilizing vibration information during operation.

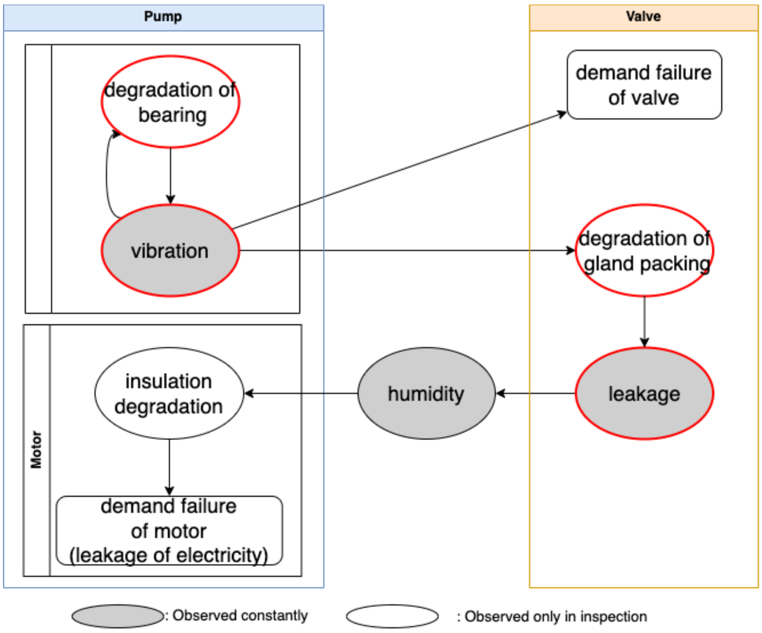

Figure 1 Dependency in the Target System

2.2. Selection of Modeling Techniques

2.2.1. Dynamic Bayesian Network (DBN)
First, a dynamic Bayesian network (DBN) was examined as a method for expressing the dependence in the target system. A Bayesian network is a method of expressing dependencies among multiple variables in a network structure, where dependencies among variables are defined by conditional probabilities and conditional probabilities are calculated based on Bayes' theorem. DBN is an extension of Bayesian network in the time axis direction and can handle time variation of random variables, and its network structure can express complex dependencies among degradation states and observed variables over time steps [2].
However, when the target system was modeled with DBN and the conditional probability table representing the deterioration progression of bearings and packings was estimated from vibration and leakage data, the following problem arose. BayesServer, a general-purpose DBN modeling tool, was unable to restrict state transitions in the direction of degradation recovery, which originally had a probability of zero, and the parameter estimation results obtained were not correct.

2.2.2. Hidden Markov Model (HMM)
Due to the above problems, we decided to use a hidden Markov model (HMM) instead of a DBN, which is a model with unobservable state variables that transition stochastically and observable stochastic outputs. When a state variable transitions only in one direction and only to the next state, as in the case of equipment degradation, it is called a Left-to-Right HMM, and constraints can be imposed to set the transition probability to zero for transitions that are not considered [3].
In general, an HMM is a model that describes a single state variable, but as an extension, there is the Coupled HMM [4], which is a model in which two or more state variables influence each other.
In HMM we can assume the degradation state of the equipment as the state variable and the data that can be obtained from sensors, etc., as the output. Then, by determining the most appropriate series of degradation states that would generate a series of data observed, we would be able to determine the actual stages of equipment degradation. This requires optimizing the parameters of the model, and once the model parameters are estimated, future state transitions can be predicted.

2.2.3. Training of HMM

Finding the model parameters (state transition probabilities, initial state probabilities, and output probabilities) that best generate a given output series in an HMM is called learning. The Baum-Welch algorithm is a method to optimize parameters by expectation maximization, updating each parameter value using forward and backward probabilities [3].

2.3. Modeling of the Target System

2.3.1. Pump and Valve Settings

In the target system, the bearing and gland packing degradation states are unobservable state variables, while vibration and leakage are observable outputs. For simplicity, the degradation states of the bearing and gland packing are assumed to transition in order of five discrete states: normal, degradation 1, degradation 2, degradation 3, and failure. Four types of vibration outputs (10µm/20µm/30µm/40µm) and two types of leakage outputs (with/without leakage) were set.

2.3.2. Dependency Modeling

In general Coupled HMMs, state variables influence each other, but in the modeling of this study, the first setup is as shown in Figure 2, where the output from one state variable, i.e., vibration, which is the output from the deteriorated state of the bearing, influences the other state variable, the deteriorated state of the valve.

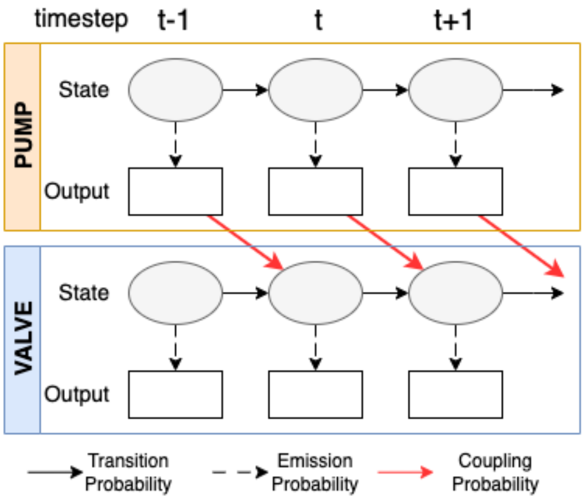

Figure 2 Outline of the Proposed Model

With reference to the Coupled HMM, the transition probability a_{ij} from state i to state j was replaced by $a_{ij} \cdot c_{ij}(V_t)$ for the packing state transition. That is, the probability of transition from state i to state j at time t is the original transition probability a_{ij} multiplied by $c_{ij}(V_t)$ according to the vibration V_t at time t. Because the probability represents a state transition, $c_{ij}(V_t)$ must satisfy Equation (1). If a_{ij} and $c_{ij}(V_t)$ can be estimated by parameter learning, the degradation rate of the packing itself can be considered from a_{ij} and the effect of vibration from $c_{ij}(V_t)$, respectively.

$$\sum_j a_{ij} \cdot c_{ij}(V_t) = 1 \tag{1}$$

3. EXPERIMENT

Parameter learning experiments were conducted with and without dependency assumptions to investigate whether the estimation of packing deterioration can be improved by utilizing vibration information during operation based on the dependency modeling described in section 3.1.
The initial state probability was assumed to be normal with probability 1 at time 0 for both the bearing and the packing. The output probabilities were set as shown in Tables 1 and 2, and these were fixed values that were not updated by learning.
Although the final goal is to estimate $\boldsymbol{a_{ij}}$ and $\boldsymbol{c_{ij}(V_t)}$ simultaneously using the Baum-Welch algorithm, in this experiment, for simplicity, $\boldsymbol{c_{ij}(V_t)}$ was fixed as given and only a_ij was estimated. Specifically, the transition

probabilities of the packing to one of the worse states were set to be 1.25, 1.5, 1.75, and 2 times higher when the vibration was 10 µm/20 µm/30 µm/40 µm, respectively, to express the dependency that "the vibration of the pump is transmitted to the valve and accelerates the deterioration of the gland packing.

$$when\ j = i + 1, \quad c_{ij}(V_t) = \begin{cases} 1.25\ (V_t = 10) \\ 1.5(V_t = 20) \\ 1.75(V_t = 30) \\ 2(V_t = 40) \end{cases} \tag{2}$$

$$\text{when } j < i, j > i + 1, \quad c_{ij}(V_t) = 0 \tag{3}$$

When j=i, $\boldsymbol{c_{ij}(V_t)}$ was calculated to satisfy Equation (1). The series of oscillations and leakages shown in Figure 3 were given as input for training.

Table 1 Symbol Emission Probability of Bearing

	Vibration(μm)			
	10	20	30	40
Normal	0.7	0.2	0.1	0
Degraded1	0.1	0.7	0.2	0
Degraded2	0	0.1	0.7	0.2
Degraded3	0	0.1	0.2	0.7
Failure	0	0	0	1

Table 2 Symbol Emission Probability of Packing

	Leakage	
	No	Yes
Normal	1	0
Degraded1	1	0
Degraded2	1	0
Degraded3	0.8	0.2
Failure	0	1

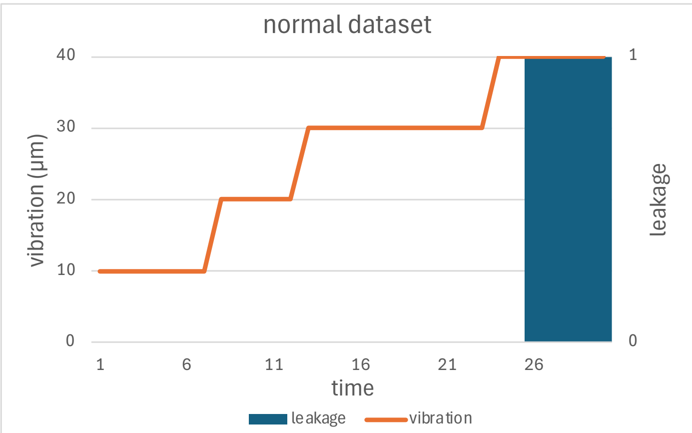

Figure 3 Input Dataset of Vibration and Leakage

4. RESULT

4.1 Results When No Dependencies Are Assumed

The results of estimating the state transition probabilities without assuming the dependency between vibration and packing, i.e., as simple HMMs independent of bearing deterioration and packing deterioration, are shown in Tables 3 and 4.

The bearing transition probabilities shown in Table 3 indicate that the bearing transitions to one of the worse states with a probability of approximately 0.1 to 0.2. The Baum-Welch algorithm is an algorithm to find the

local optimum solution, but even when the initial values were changed, the results were consistent to about two decimal places.
In Table 4, the values in rows 1, 2, and 3 are consistent. In this study, the leakage data, which is the output series of the packing, is only switched once between no leakage and leakage, and the progression of deterioration between normal, degradation 1, degradation 2, and degradation 3 can only be estimated under the condition that deterioration progresses at a constant rate.

Table 3 Re-estimated Transition Matrix of Bearing

		State of Bearing[t]				
		Normal	Degraded 1	Degraded 2	Degraded 3	Failure
State of Bearing [t-1]	Normal	0.863	0.137	0	0	0
	Degraded1	0	0.794	0.206	0	0
	Degraded2	0	0	0.907	0.093	0
	Degraded3	0	0	0	0.085	0.915
	Failure	0	0	0	0	1

Table 4 Re-estimated Transition Matrix of Packing

		State of Packing [t]				
		Normal	Degraded 1	Degraded 2	Degraded 3	Failure
State of Packing [t-1]	Normal	0.875	0.125	0	0	0
	Degraded1	0	0.875	0.125	0	0
	Degraded2	0	0	0.875	0.125	0
	Degraded3	0	0	0	0.200	0.800
	Failure	0	0	0	0	1

4.2 Results When Dependencies Are Assumed

Assuming a dependency between vibration and packing, the state transition probabilities of the packing states were estimated as shown in Table 5. The results for the bearing are similar to those in Section 4.1, Table 3, which does not consider dependence because external influences such as packing are not taken into account. In Table 5, different transition probability values are obtained for each degradation stage, unlike the case where the dependence was not considered. This result is different from Table 4 because the parameters were estimated such that the degradation was accelerated in response to the vibration from the pump at each time step, leading to the leakage at time 25.
Considering actual deterioration, it is difficult to assume that deterioration always progresses at a constant rate, and it is possible that deterioration may accelerate depending on external conditions. The results of this experiment indicate the possibility of estimating the condition of valve packing degradation, for which only leakage data can be obtained, by taking into account the effect of vibration that accelerates degradation.

Table 5 Re-estimated Transition Matrix of Packing with Dependency

		State of Packing [t]				
		Normal	Degraded 1	Degraded 2	Degraded 3	Failure
State of Packing [t-1]	Normal	0.884	0.116	0	0	0
	Degraded1	0	0.866	0.134	0	0
	Degraded2	0	0	0.894	0.106	0
	Degraded3	0	0	0	0.823	0.177
	Failure	0	0	0	0	1

5. DISCUSSION

The results of this experiment indicate that it may be possible to estimate the condition of valve packing deterioration, for which only leakage data is available, by taking into account the effects of vibration, which accelerates deterioration.
The challenge in modeling the system is to make the equipment configuration more detailed and realistic. Degradation is modeled in discrete steps, but it is desirable to link this to actual degradation phenomena.
One of the challenges in modeling dependence is to improve the algorithm so thata_{ij} and $c_{ij}(V_t)$are estimated simultaneously. As mentioned earlier, we believe this would allow for the extraction of external influences such as vibration.
We would also like to consider how the modeling of dependence proposed in this model can be applied to real systems in order to apply it to state-based maintenance and other activities.

6. CONCLUSION

In this study, a model was proposed to estimate the condition of a system consisting of pumps and valves as an example of a system consisting of multiple components, taking into account degradation dependence. Experiments using the model showed that the modeling of dependence enables inference using data from related equipment and may improve the state estimation of equipment with poor degradation data.
In the future, we plan to improve the proposed model, focusing on solving the issues described in the previous chapter.

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