MCMC-based Efficient Maintenance Plan Decision

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ABSTRACT

In recent years, it has been an essential policy to monitor real-time health states of facilities and determine when to perform maintenance in order to ensure the high operation ratio and improve work efficiency. In this paper, target facilities diagnose their own health states by analyzing time-series sensor data and transmit warning data and failure data to the monitoring center. These data include date and time of occurrence and warning/failure code which identifies the factor. Utilizing these data, we propose an MCMC-based maintenance plan decision to reduce the failures and the workloads. Firstly, state-based warning patterns which are composed of several warning codes are extracted. At that time, to avoid the state explosion, only warning patterns which are closely related to failure occurrence are extracted based on the time interval from warning states to failure state. Secondly, warning patterns are modeled based on N-th order Markov model. Finally, maintenance plan is decided based on failure probability. Experiment to evaluate whether the facilities can be maintained before failure occurs proved that this approach could actually reduce the number of failures and the frequency of dispatches of maintenance workers.

1. INTRODUCTION

The advanced maintenance methods have been required to ensure the high operation ratio because building facilities have become more extensive and complicated. Therefore, most maintenance companies which perform routine inspections and repairs provide remote monitoring service in recent years. And they monitor the health states of the facilities continuously.

The target facilities diagnose their own health states by analyzing time-series sensor data and transmit event data to the monitoring center as needed. Because the transmission capacity of a data communication line is limited, event data are transmitted only when a certain error occurs. At the monitoring center, these event data are stored in failure DB which is composed of warning data and failure data. As illustrated in Fig. 1, warning data are transmitted when sensor data exceed a threshold of warning even though facility state is normal. In this case, because the facility restarts and runs a trial, maintenance workers are urged to prepare for the maintenance. On the other hand, failure data are transmitted when sensor data exceed a threshold of failure. In this case, because the facility stops for breakdown, the workers are urged to perform on-site maintenance surely.

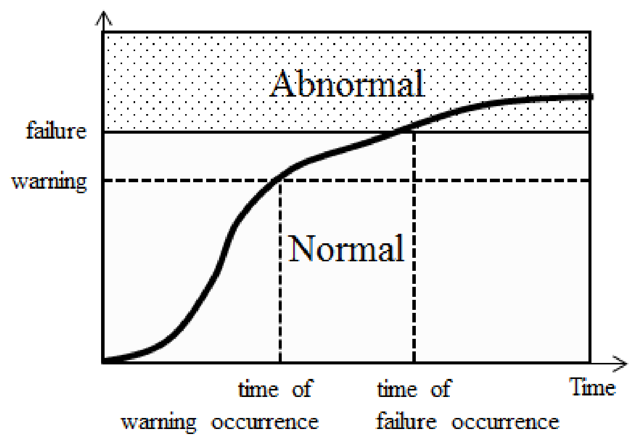

Fig. 1. Warning and failure occurrence in sensing data

To reduce the failures, workers are expected to perform maintenance early every time warnings occur. However, because the number of workers is also limited, it is actually difficult to perform maintenance at any time. Moreover, even if workers perform maintenance early in accordance with the order of warning occurrences, failure may eventually occur because the failure doesn't always occur in accordance with the order of warning occurrences (Fig. 2).

From the above, to avoid failure, it is expected to perform efficient maintenance in a limited number of workers. This paper proposes a maintenance plan decision approach based on MCMC which models time intervals from several warning states to failure state (Fig. 3).

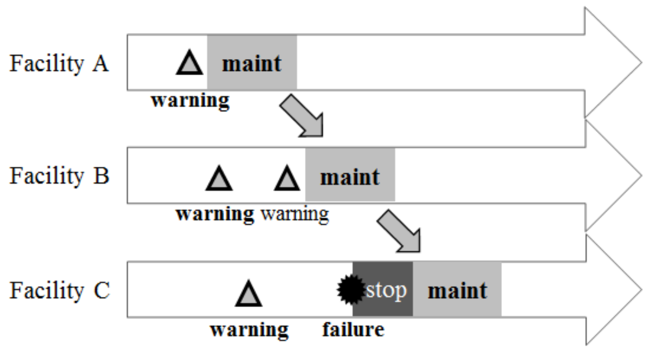

Fig. 2. Example of maintenance based on the order of warning occurrences
As a result, facility C becomes failure state.
(maint means maintenance)

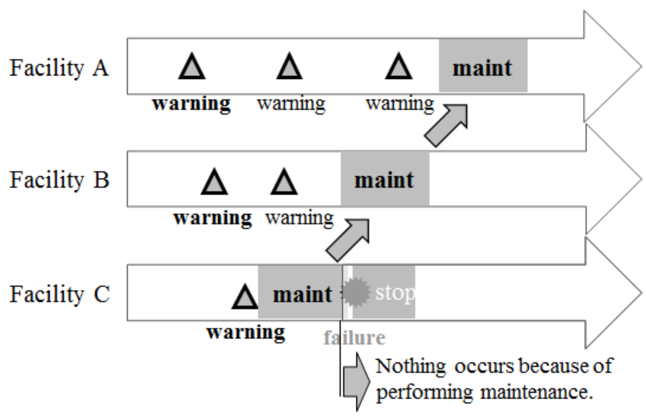

Fig. 3. Example of maintenance based on proposed approach
As a result, no facility becomes failure state.
(maint means maintenance)

2. RELATED WORKS

As an advanced maintenance, several approaches have been already proposed such as proactive maintenance [1] and predictive maintenance [2]. Proactive maintenance means repairing immediately before a customer recognizes, and predictive maintenance means repairing immediately before a failure occurs. Among these maintenance approaches, predictive maintenance is considered to be enough approach to satisfy building owners which desire to ensure the high operation ratio.

To perform the predictive maintenance, Prognostics and Health Monitoring (PHM) technique has emerged as a key technology to detect and monitor the health state and warning state by sensors incorporated in facility[3]-[5]. And PHM has applied various mechanical systems such as automotive industry [6], aeronautics [7]-[8], civil engineering [9], and heavy industry [10]. In general, PHM consists of 4 functions, (i) health sensing function, (ii) health diagnosing function, (iii) health prognosing function, and (iv) health managing function. This paper discusses mainly health prognosing function.

To solve and conduct the health prognosing, there are many approaches. The authors in [11] provide a Remaining Useful Life (RUL) prediction approach based on Kalman Filter with dynamic curve fitting. In [12], the authors present a neural network modeling about the problem of actuator fault detection and failure progression. The authors in [13] use a fuzzy similarity analysis to determine the suitability correction factor to current environmental conditions for lifetime prediction. In [14], the authors present a gearbox prognosis approach based on continuous hidden Markov model and support vector machine. And statistical approaches are also proposed to decide maintenance plan by predicting the facilities' lifetime in [15]. In [15], maintenance plan is decided based on failure probability which is extracted from the time interval from single warning to single failure. So, it is not considered in case of transiting from several kinds of warning states to a failure state.

In this paper, we apply a statistical MCMC approach because it can model the several kinds of state transitions.

3. MARKOV CHAIN MONTE CARLO ALGORITHMS (MCMC)

MCMC is a Monte Carlo method using Markov chains sampling. The Markov chain is a sequence of random variables $x_0, x_1, x_2 ...$ with the Markov property, namely that the probability of moving to the next state depends only on the present state and not on the previous states as Eq. (1).

$$P(X_{n+1} = x \mid X_n = x_n, , X_0 = x_0) = P(X_{n+1} = x \mid X_n = x_n)$$
$$\text{where} \quad x_0, x_1, , x_n \in S \qquad (1)$$

To model the case of transition from several kinds of warning states to failure state, it is needed to apply model depending not only on the present state, but also on the previous states.

Then, in this paper, we apply the N-th order Markov model as Eq. (2) which is expressed by expanding Eq. (1).

$$P(X_{n+1} = x \mid X_n = x_n, , X_0 = x_0) = P(X_{n+1} = x \mid X_n = x_n, , X_{n-N+1} = x_{n-N+1}) \qquad (2)$$

Next, sampling algorithms based on MCMC are mainly divided into two methods, Metropolis algorithm and Gibbs sampling. This paper utilizes Metropolis algorithm.

4. PROPOSED APPROACH

At the monitoring center, event data which consist of warning data and failure data collecting from respective facilities are stored in failure DB. As shown in TABLE I. failure DB consists of Reception ID which identifies event data uniquely, Date and Time which means date and time of occurrence, Facility ID which identifies facility uniquely, Model Type which means the model of facility, W/F which classifies the event types of data as either warning or failure, and W/F Code which identifies the factor.

TABLE I. DETAILS OF FAILURE DB

Field	Example	Info
Reception ID	1	primary key
Date and Time	10:30:50 04-01-2010	date and time of occurrence
Facility ID	123456789	unique identification of facility
Model Type	A-Model	facility model
W/F	W	warning or failure
W/F Code	1111	factor code which causes W/F 1111:Inverter overload

It is natural that the possibility of failure occurrence differs depending on facility structures, machine parts, and factors. Therefore, we construct the model for each failure codes collecting from facilities of the same Model Type.

4.1. State based Modeling of Facilities

Fig. 4 shows an example of time-series transition of a facility state from several warnings to a failure. Some failures occur resulting from single warning occurrence (case1); others occur resulting from several warning occurrences (case2). In general, a state explosion problem arises if all combinations of warning states are modeled. To avoid this problem, only important combinations of warning states should be extracted and modeled. In this paper, we define warning pattern as combination of warnings composed of several warning codes, and model only warning pattern closely related to failure occurrence. To extract only important warning pattern, we focus on both time interval from respective warning states to failure state and failure probability of the respective warning states.

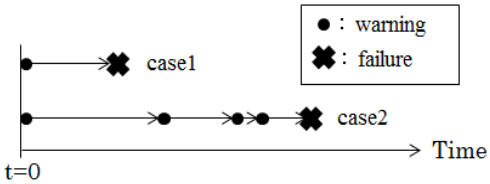

Fig. 4. Time course state transition

4.1.1. Warning Patterns Closely Related to Failure Extraction Method

The strength of relevance with failure state is decided by using the rate of change of failure probability (P_c). P_c is calculated as Eq. (3) when conditional probability of failure given warning x_n is expressed as $P_{xn}= P(X_{n+1}=e|X_n=x_n,,,X_0=x_0)$.

$$P_c(x_n) = \frac{(P_{x_{n+1}} - P_{x_n})}{P_{x_n}} \times 100 \tag{3}$$

As illustrated in Fig. 5, warning patterns are created by tracing back from failure state to respective warning states (Pattern 1, Pattern 2, and Pattern 3). *Pc* is calculated using warning pattern's conditional probability. At that time, P_c is compared with Relation Threshold (*RT*) to decide whether high or low relevance with failure state. In other words, when P_c exceeds *RT*, the warning pattern is decided as high relevance with failure state.

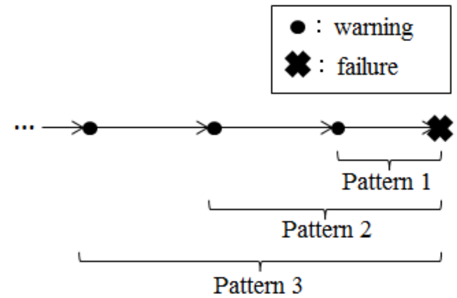

Fig. 5. Warning patterns from warning states to falure state

In this paragraph, the warning pattern extraction method is described according to Fig. 5. At First, P_c is calculated using conditional probability of Pattern 1 whose warning state is temporally close to failure state and that of Pattern 2 to which the warning states are added by one state compared with Pattern 1. Then, P_c is compared with *RT*. As a result, when *Pc* falls below the *RT*, it is considered that the newly added warning state of Pattern 2 is not directly related to the failure state because the rate of change is small. So, Pattern 2 is decided to have low relevance with failure state. Then warning pattern is extracted as Pattern 1. On the other hand, when *Pc* exceeds the *RT*, it is considered that the newly added warning state of Pattern 2 may be directly related to the failure state because the rate of change is big. So, Pattern 2 is decided to have high relevance with failure state. Next, P_c is calculated using conditional probabilities of Pattern 2 and Pattern 3 to which the warning states are added by one state compared with Pattern 2. Then, P_c is compared with *RT*. This processing is repeated until P_c falls below the *RT*. From the above, warning patterns closely related to failure are extracted for each failure codes.

4.1.2. Modeling based on MCMC

The tendency of likeliness of the failure occurrence is influenced not only by the number of warning states, but also by elapsed time from warning occurrence. Then, in this paper, warning patterns are modeled according to the Timed MCMC.

4.2. Maintenance Plan Decision Approach

As following steps, Metropolis algorithm is used for calculating the number of failures for each elapsed time from warning states, and the failure probability distribution is created.

1. First warning state of the warning pattern is chosen as initial value $x_{0.}$
2. Current warning state is defined as x_n, and warning or failure state transiting from x_n is chosen as x'.
3. The probability ratio is calculated from the probability of x' and that of x_n as follows.

$$r = P(x') \big/ P(x_n)$$

4. A uniform random number R is generated within a range of $[0,1]$.
5. When r exceeds R, next warning or failure state is set as x'. On the other hand, when r falls below R, current warning state is set as x'. Then elapsed time is incremented.
6. Step2 to 5 is repeated until time becomes T. When failure occurs, the time interval from initial warning state to failure state is recorded.
7. Using time interval extracted through Step6, failure probability distribution is created and Step2 to 6 is repeated until failure probability distribution is converged.

Through this procedure, it can be possible to calculate failure probability considered several warning states. At that time, Maintenance Threshold (MT) which decides whether workers should perform maintenance or not is defined. When failure probability exceeds MT, it is considered that the facility should be performed maintenance because of high possibility of becoming failure state.

5. EVALUATION

5.1. Experimental Outline

We conduct an experiment to evaluate the effectiveness of our approach, which considers not only for single warning state, but also for several warning states transiting to failure state. This time, we use the actual data stored in failure DB at the monitoring center. Details of experimental data are shown in TABLE II.

TABLE II. DETAILS OF EXPERIMENTAL DATA

Learning Data	Period	One year
	Data Amount	8 thousand warnings and failures data
Warning Codes		30 kinds of warning codes
Evaluation Data	Period	One year
	Data Amount	12 thousand warnings and failures data

Next, four approaches are experimented as follows. In fact, approach 1 and approach 2 are used for evaluation index, and proposed approach is compared with comparative approach. In this experiment, workers are assumed to go on site and perform maintenance when the failure probability of the facility, which is calculated based on MCMC exceeds MT. Moreover, the time required for arriving at the site and the work time are also taken into consideration.

- Comparative Approach: Perform maintenance based on MCMC (1st order Markov model).
- Proposed Approach: Perform maintenance based on MCMC (N-th order Markov model).
- Approach 1: Perform maintenance every time warning occurs.
- Approach 2: Perform maintenance after failure occurs.

When we define the number of failures F and the number of dispatches of workers D, F and D which are calculated using approach 1 and approach 2 are also defined as F_1, D_1 and F_2, D_2. The two evaluation indexes are shown in TABLE III. Evaluation index (i) means the ratio of the number of facility failures (ratio of FF) to the number of facilities that can be performed maintenance before failure occurs. So, it represents that the closer the value of the ratio of FF is to 0, the fewer the failures become. And evaluation index (ii) means the ratio of the number of dispatches of workers (ratio of DW) to the number of facilities that don't become failure eventually. So, it represents that the closer the value of the ratio of DW is to 0, the fewer the workloads become.

TABLE III. EVALUATION INDEX

Evaluation Index
(i) Ratio of the number of failures (Ratio of FF): $\dfrac{F - F_1}{F_2 - F_1}$
(ii) Ratio of the number of dispatches (Ratio of DW): $\dfrac{D - D_2}{D_1 - D_2}$

5.2. Experimental Results

In this experiment, *RT* is set to 20 and *MT* is set to 0.1, and 45 warning patterns are extracted. Moreover, the time required for arriving at the site and the work time are set as fixed value regardless of a place where target facility is installed. Fig. 6 shows the result of the ratio of FF and Fig. 7 shows the result of the ratio of DW. As shown in Fig. 6, proposed approach can reduce the number of failures and as show in Fig. 7, it can reduce the frequency of dispatches of workers.

Next, according to the proposed approach, the ratio of FF and ratio of DW due to the differences in *MT* are shown in Fig. 8 and Fig. 9. As a result, it is found that the relation between a ratio of FF and a ratio DW is a trade-off. When *MT* is set to 0.1, about half of the total number of facilities can be performed maintenance before failure occurs, and about 80% of the total number of dispatches of workers can be reduced. Moreover, it is found that the ratio of FF and ratio of DW are strongly influenced by *MT*, rather than the number of workers in this case.

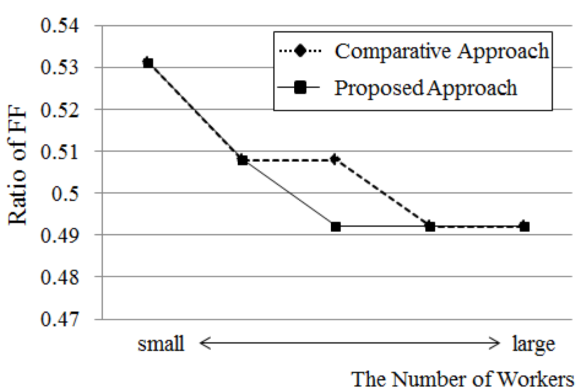

Fig. 6. The result of the ratio of FF

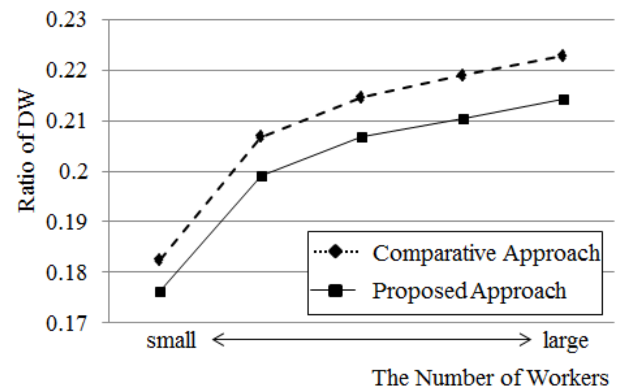

Fig. 7. The result of the ratio of DW

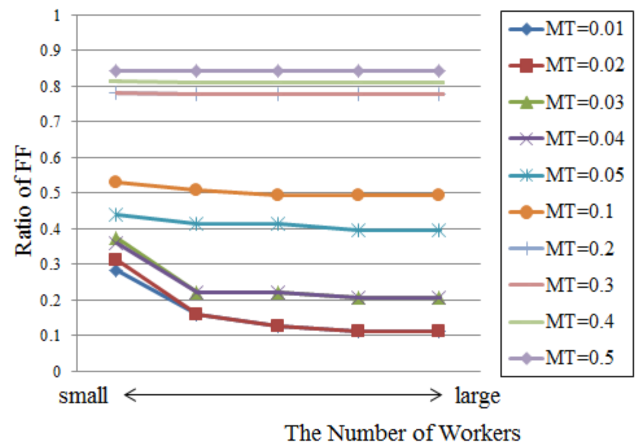

Fig. 8. The result of the ratio of FF due to the diffrence in *MT*

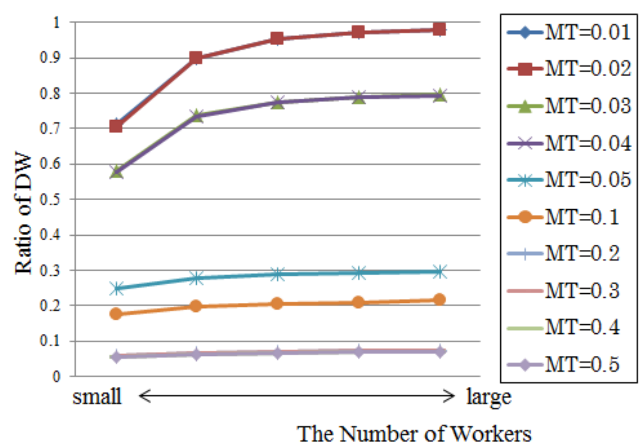

Fig. 9. The result of the ratio of DW due to the diffrence in *MT*

6. MAINTENANCE PLAN DECISION SUPPORT TOOL

Based on proposed approach, we developed the maintenance plan decision support tool (Fig. 10). This tool provides simulation environment by setting the number of workers, the time required for arriving at the site and the work time. This tool visualizes both the maintenance status of the facility which warning occurred and the worker status. Left table means a list of facilities being warning states. And based on failure probability calculated using MCMC, the list is arranged in order of high possibility of failure occurrence. When failure occurs, the background color of target facility's row is changed. Right table means a list of workers representing whether they are working or not. If workers perform maintenance, the working icons are shown. Using this tool, user can confirm the maintenance plan changing the parameter.

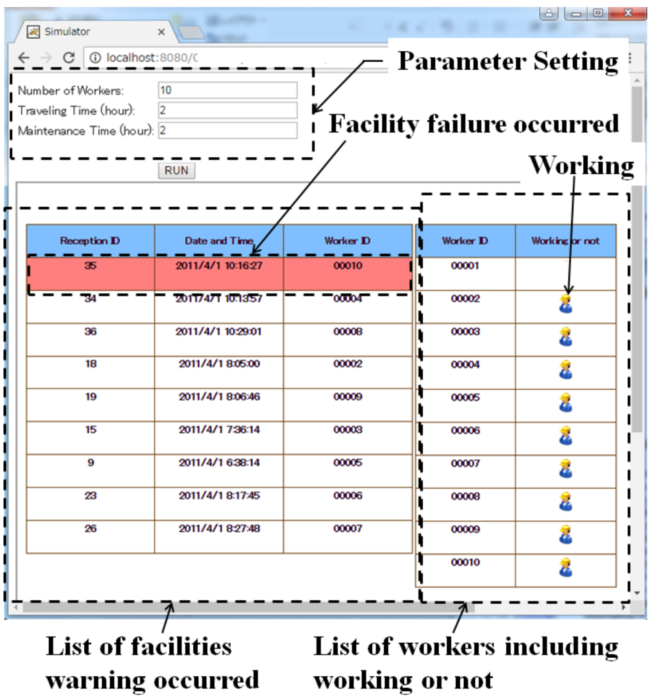

Fig. 10. Outline of maintenance plan decision support tool

7. CONCLUSION

In this paper, to reduce the failures and the workloads, we proposed an MCMC-based maintenance plan decision in consideration of several warning states transiting to failure state. Moreover, we developed the maintenance plan decision support tool, which visualized both the maintenance status of the facility warning occurred and the worker status. Firstly, to decide the maintenance plan, state-based warning patterns which meant combinations of warnings composed of several warning codes were extracted. At that time, only warning patterns which were closely related to failure were extracted focusing on both time intervals from respective warning states to failure state, and failure probability of the respective warning states. Secondly, warning patterns were modeled based on N-th order Markov model. Finally, maintenance plan was decided based on failure probability. We conducted an experiment to evaluate the effectiveness of our approach comparing with an approach based on MCMC using 1st order Markov model. As a result of experiment, it was proved that our proposed approach could actually reduce the number of failures and the frequency of dispatches of maintenance workers.

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