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# ON-LINE RESIDUAL LIFE PREDICTION INCLUDING OUTLIER ELIMINATION FOR CONDITION BASED MAINTENANCE

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Abstract. *A method of on-line residual life prediction is proposed for condition based maintenance of industrial equipment. With on-line monitoring of condition of the industrial equipment, the residual life is evaluated by using on-line prediction of the equipment deterioration. The deterioration prediction is based on an on-line identification of the mathematical model of deterioration process. To improve the accuracy of the deterioration prediction, outlier elimination technique is introduced. The proposed method was applied to actual data of rotating equipment in a thermal power plant and the results verified the effectiveness of the proposed method.*
**Keywords:** On-line prediction, Outlier elimination, Deterioration prediction, Residual life prediction, Condition based maintenance

1. **Introduction.** In a lot of industrial systems such as power stations, steel plants and petrochemical plants, time based maintenance (TBM), i.e., periodical maintenance, is adopted as a maintenance policy. The growing cost of maintenance is a serious problem in industry, and the reduction of maintenance cost is eagerly desired while keeping the system reliability. The main assumption in TBM is that, the chance of a equipment failure depends on the age of the equipment, i.e., the failure rate of the equipment will increase with time. If correlation between the equipment failure and the equipment age is not much high, TBM is not an effective strategy for reducing the life cycle cost including maintenance, repair and replacement costs of the industrial systems.

The appropriate timing of maintenance according to the deterioration of the equipment can reduce the life cycle cost. Then, the excess maintenance cost decided by TBM can be avoided. In order to reduce the life cycle cost of industrial systems, condition based maintenance (CBM) has been introduced. In CBM, the condition of the equipment is monitored and timing of the maintenance action is decided based on the condition of the equipment [1]. A lot of researches concerning about CBM have been carried out, for example, the on-line fault identification and classification of rolling element bearing based on time-varying autoregressive spectrum [2], the reliability-centered predictive maintenance scheduling for a continuously monitored system [3], the fuzzy decision-making applied to the signal-based diagnostic algorithms [4], the residual life predicting based on neural networks [5], the residual life predictions of ball bearings based on self-organizing map and back propagation neural network methods [6], the utilising statistical residual life estimates of bearing to quantify the influence of preventive maintenance actions [7] and the asset residual life prediction model based on expert judgments [8]. When these methods are applied to the industrial systems, the expert judgment based method [8] requires accumulation of expert judgement results, and the neural network based or fuzzy based methods [2, 4, 5, 6] require the training data for neural network learning or sufficient data for making fuzzy decision rules, and the maintenance scheduling method [3] requires the system hazard rate as a function of the system condition.

In this research, an on-line residual life prediction based on the deterioration prediction of the equipment is proposed in order to determine an appropriate timing of the maintenance action. In the other research on residual life prediction [9], the life of a piece of production equipment is divided into two stages, i.e., the normal working stage and the failure delay period, and a probability model is introduced to predict the initiation point of the defective stage and the remaining life based on available condition monitoring information, which is close to the problem identified in this research. However, the method is an off-line algorithm and it is difficult to implement in an on-line fashion, especially for parameter estimation of a probability model.

On-line residual life prediction can realize the determination of the appropriate timing of maintenance. Feature of the proposed method is the combination of the on-line monitoring and the on-line residual life prediction of the equipment for CBM. The mathematical model of the deterioration is introduced for the deterioration prediction. To improve the accuracy of the deterioration prediction, the outlier judgement in on-line monitoring data is also adopted.

## 2. Condition Based Maintenance of Equipment.

**2.1. Time based maintenance and condition based maintenance.** Traditional preventive maintenance policy is a time based maintenance (TBM), i.e., the maintenance action is carried out at constant time period. TBM is effective for the age-related failures, where the failure rate increases with time. According to the investigations on United Airlines aircraft components, the U.S. Navy and various industries, only about 15% to 20% of equipment failures are age-related. The other 80% to 85% of equipment failures are based totally on the effects of random events that happen in the system [10].

In the condition based maintenance (CBM), the equipment is monitored periodically and the decision making of the maintenance action is based on the condition of the equipment. By monitoring the condition of equipment, more appropriate maintenance can be utilized and hence the life cycle cost of the systems including maintenance, repair and replacement costs will be reduced.

**2.2. Assumptions of deterioration and deterioration management values.** The measurement data for monitoring the condition of the equipment are called as "deterioration management values". Assumptions for the development of the on-line residual life prediction are summarized as follows:

(1) Deterioration is progressed with time after defect may be initiated.
(2) Condition of the equipment is monitored by measuring deterioration management values.
(3) Condition of the equipment never recover without repair or replace, i.e., the deterioration is monotonically progressed.
(4) On-line measurement of the deterioration management values is available.
(5) Deterioration management values may include measurement errors.
(6) Mathematical model of the deterioration process is given.

**2.3. Condition based maintenance by on-line residual life prediction.** Figure 1 shows the flowchart of the deterioration management procedure where the deterioration management values of the equipment are obtained in an on-line fashion. The on-line deterioration management is divided into three parts. The first part is outlier judgement

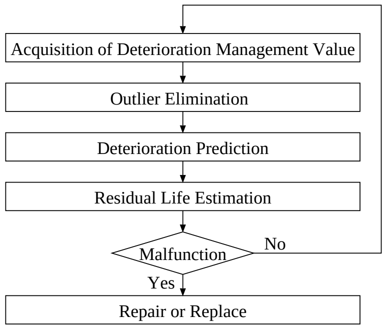
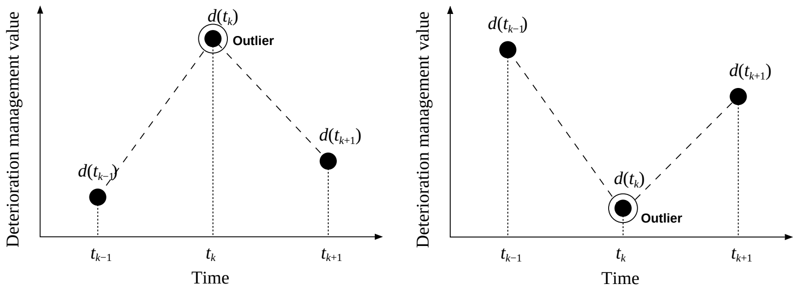



FIGURE 1. Flowchart of deterioration management




(a) Pattern 1 (up and down) (b) Pattern 2 (down and up)

FIGURE 2. Concept of outlier judgement in deterioration management values

of the deterioration management values, the second part is the deterioration prediction by using the deterioration model, and the last part is the residual life prediction by using the deterioration prediction. According to three steps, the deterioration management of the equipment can be carried out.

## 3. On-Line Deterioration Prediction and Residual Life Prediction.

**3.1. Outlier judgement of deterioration management values.** The deterioration management values contain certain amount of data deviated from the trend of data. In this research, such data are referred to as "outliers". The outliers make errors in the equipment diagnosis, because deterioration tendency is disturbed by the outliers and the mathematical model of the deterioration management value is drifted away by the outliers. If the outliers are appropriately eliminated from the deterioration management values, the accuracy of deterioration model will be improved. Hence, the outlier judgement is important for the equipment diagnosis.

The conditions of the on-line outlier judgement are classified into two patterns as shown in Figure 2 [11]. These patterns are derived from the assumption, i.e., the fact that deterioration never be recovered without repair or replace (Assumption (2) in Section 2.2).

3.1.1. *Pattern 1.* In Pattern 1, the deterioration management value initially increases and then, it decreases monotonously (see Figure 2(a)). The deterioration management value $d(t_k)$ at time $t_k$ is decided as an outlier when the conditions:

$$d(t_k) - d(t_{k-1}) \geq m_p + r_p^u \sigma_p \tag{1}$$

$$d(t_{k+1}) - d(t_k) \leq m_n - r_n^u \sigma_n \tag{2}$$

are satisfied. Here, $m_p$ and $\sigma_p$ are mean and standard deviation of positive values of the time difference of the deterioration management value, respectively, $m_n$ and $\sigma_n$ are mean and standard deviation of negative values of the time difference of the deterioration management value, respectively. Here, $r_p^u$ and $r_n^u$ are coefficients of the respective confidence levels.

3.1.2. *Pattern 2.* In Pattern 2, the deterioration management value initially decreases and then it increases monotonously (see Figure 2(b)). The deterioration management value $d(t_k)$ at time $t_k$ is decided as an outlier when the conditions:

$$d(t_{k+1}) - d(t_k) \leq m_n - r_n^d \sigma_n \tag{3}$$

$$d(t_k) - d(t_{k-1}) \geq m_p + r_p^d \sigma_p \tag{4}$$

are satisfied. Here, $r_n^d$ and $r_p^d$ are coefficients of the respective confidence levels.

Means and standard deviations in (1)-(4) are calculated by using previously collected data of the deterioration management values. The confidence levels are determined such that the outliers in the previously collected data can be detected.

### 3.2. **Deterioration prediction.**

3.2.1. *Deterioration model.* In order to predict future condition of the equipment, the mathematical model of deterioration is introduced as

$$y(t_n) = f(\boldsymbol{z}(t_n); \boldsymbol{a}) = \boldsymbol{z}^T(t_n)\boldsymbol{a} \tag{5}$$

where $y(t_n)$ is the model output at time $t_n$ which corresponds to the deterioration management value $d(t_n)$, $\boldsymbol{z}(t_n)$ is a state variable and $\boldsymbol{a}$ is a model parameter. Here, the mathematical model is assumed to be linear with respect to the model parameter $\boldsymbol{a}$. If the deterioration mechanism and/or characteristics are known, the mathematical model which reflects the mechanism and/or characteristics are used. If no information about the deterioration characteristics is obtained, time series models such as AR, ARMA and ARIMA can be used for the mathematical model (Assumption (6) in Section 2.2).

3.2.2. *On-line estimation of deterioration model.* The loss function for the model identification is given by

$$J(t_n) = \sum_{k=1}^{n} \rho^{n-k} \left(y(t_k) - d(t_k)\right)^2 \tag{6}$$

where $\rho$ $(0 < \rho \leq 1)$ is a forgetting factor and $d(t_k)$ is the deterioration management value at time $t_k$. The exponentially weighted recursive least squares method is applicable to estimate the model parameter given by

$$\boldsymbol{a}(t_n) = \boldsymbol{a}(t_{n-1}) + \frac{\boldsymbol{P}(t_{n-1})\boldsymbol{z}(t_n)}{\rho + \boldsymbol{z}^T(t_n)\boldsymbol{P}(t_{n-1})\boldsymbol{z}(t_n)} \left(y(t_n) - \boldsymbol{z}^T(t_n)\boldsymbol{a}(t_{n-1})\right) \tag{7}$$

$$\boldsymbol{P}(t_n) = \frac{1}{\rho}\left(\boldsymbol{P}(t_{n-1}) - \frac{\boldsymbol{P}(t_{n-1})\boldsymbol{z}(t_n)\boldsymbol{z}^T(t_n)\boldsymbol{P}(t_{n-1})}{\rho + \boldsymbol{z}^T(t_n)\boldsymbol{P}(t_{n-1})\boldsymbol{z}(t_n)}\right).$$

If the deterioration management value $d(t_{n-1})$ at time $t_{n-1}$ is judged as an outlier, the bad influence on the estimation of the model parameter must be eliminated. Then, the deterioration management value $d(t_{n-1})$, the affected model parameter $\boldsymbol{a}(t_{n-1})$ and $\boldsymbol{P}(t_{n-1})$ can not be used for the update of the model parameter in Equation (7). Hence, these values at time $t_{n-2}$ instead are used for the update of the model parameter.

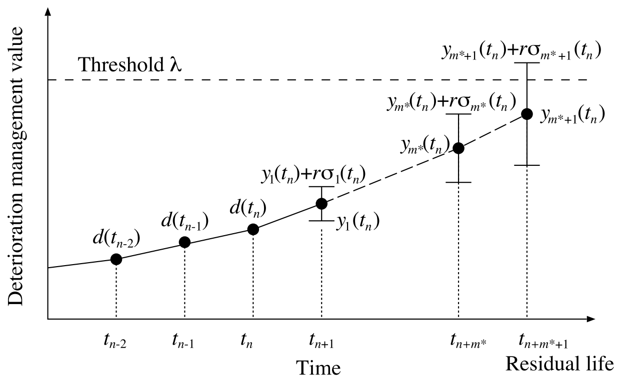
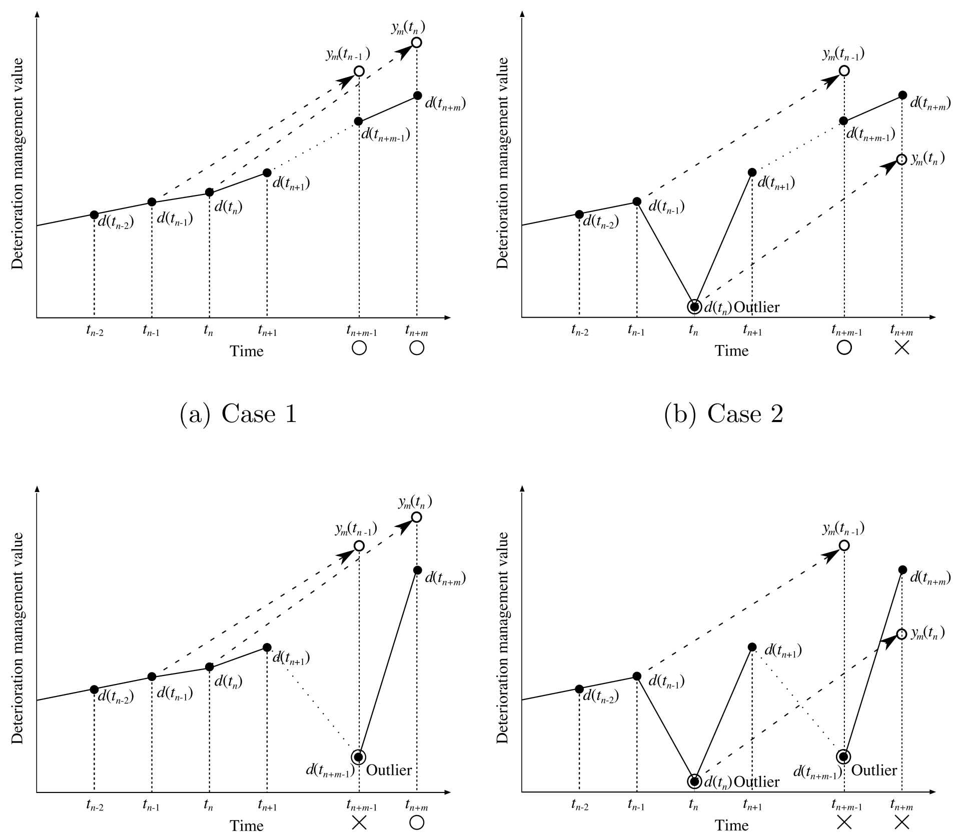



FIGURE 3. Concept of residual life prediction




(a) Case 1 (b) Case 2

(c) Case 3 (d) Case 4

FIGURE 4. Four cases for calculation of standard deviation of the prediction errors

3.2.3. *Prediction of deterioration management values.* Figure 3 shows the conceptual diagram of prediction of the deterioration management value. The $m$ step ahead predicted value $y_m(t_{n+m})$ of the deterioration management value at time $t_{n+m}$ is calculated by using mathematical model as

$$y_m(t_n) = f(\boldsymbol{z}(t_{n+m}); \boldsymbol{a}(t_n)) = \boldsymbol{z}^T(t_{n+m})\boldsymbol{a}(t_n), \quad m = 1, \dots, l. \tag{8}$$

## 3.3. **On-line residual life prediction.**

3.3.1. *Calculation of confidence interval.* The confidence interval of the predicted value $I_m(t_n)$ is evaluated by using standard deviation $\sigma_m(t_n)$ of the prediction error $e_m(t_n) = y_m(t_{n-m}) - d(t_n)$ of the deterioration management values as

$$I_m(t_n) = y_m(t_n) + r\sigma_m(t_n), \quad m = 1, \ldots, l \tag{9}$$

$$\sigma_m(t_n) = \sqrt{\frac{S_m(t_n)}{n_m(t_n)}}, \quad m = 1, \ldots, l. \tag{10}$$

Here, the prediction error $e_m(t_n)$ is assumed to be independently and identically distributed as $N(0, \sigma_m^2(t_n))$ and the coefficient $r$ is given as predetermined confidence level.

Outliers in the deterioration management values generally have harmful effects on estimation of standard deviation of the prediction errors. Hence, the outliers are eliminated from the estimation of standard deviation as follows (see Figure 4).

Case 1. In Case 1, no outliers exist. Then, $S_m(t_n)$ and $n_m(t_n)$ in Equation (10) are updated by

$$\begin{aligned} S_m(t_n) &= \rho S_m(t_{n-1}) + (e_m(t_n))^2 \\ n_m(t_n) &= \rho n_m(t_{n-1}) + 1. \end{aligned} \tag{11}$$

Case 2. In Case 2, $d(t_n)$ is the outlier, then $e_m(t_n) = y_m(t_n) - d(t_{n+m})$ cannot be used for an evaluation of standard deviation. Hence, $S_m(t_n)$ and $n_m(t_n)$ are updated by

$$\begin{aligned} S_m(t_n) &= S_m(t_{n-1}) \\ n_m(t_n) &= n_m(t_{n-1}). \end{aligned} \tag{12}$$

Case 3. In Case 3, $d(t_{n+m-1})$ is the outlier, then $e_m(t_{n-1}) = y_{m-1}(t_n) - d(t_{n+m-1})$ cannot be used for an evaluation of standard deviation. Hence, $S_m(t_n)$ and $n_m(t_n)$ are updated by

$$\begin{aligned} S_m(t_n) &= \rho S_m(t_{n-2}) + (e_m(t_n))^2 \\ n_m(t_n) &= \rho n_m(t_{n-2}) + 1. \end{aligned} \tag{13}$$

Case 4. In Case 4, both $d(t_n)$ and $d(t_{n+m-1})$ are the outliers, then both $e_m(t_n) = y_m(t_n) - d(t_{n+m})$ and $e_m(t_{n-1}) = y_{m-1}(t_n) - d(t_{n+m-1})$ cannot be used to evaluate standard deviation. Hence, $S_m(t_n)$ and $n_m(t_n)$ are updated by

$$\begin{aligned} S_m(t_n) &= S_m(t_{n-2}) \\ n_m(t_n) &= n_m(t_{n-2}). \end{aligned} \tag{14}$$

3.3.2. *On-line residual life prediction.* If the upper bound of a confidence interval $I_m(t_n)$ in Equation (9) for a given confidence level exceeds a threshold value $\lambda$, the rotating equipment seems to be deteriorated as it contains some defects. Then the residual life $m^*$ of the equipment can be evaluated by

$$m^* = \arg\left(\min_{m(=1,2,\ldots,l)} (I_m(t_n) > \lambda)\right) - 1. \tag{15}$$

3.3.3. *Condition based maintenance using residual life prediction.* Figure 5 shows the detailed flowchart of the proposed deterioration management. The deterioration management is carried out by the following procedure.

(1) Acquire the deterioration management value $d(t_n)$ at time $t_n$.
(2) Judge the outlier by using Equations (1)-(4).
(3) If outlier exists, eliminate the outlier $d(t_{n-1})$ and update the deterioration model parameters by using Equation (7), then go to Step 5.
(4) Update the deterioration model parameters by using Equation (7).

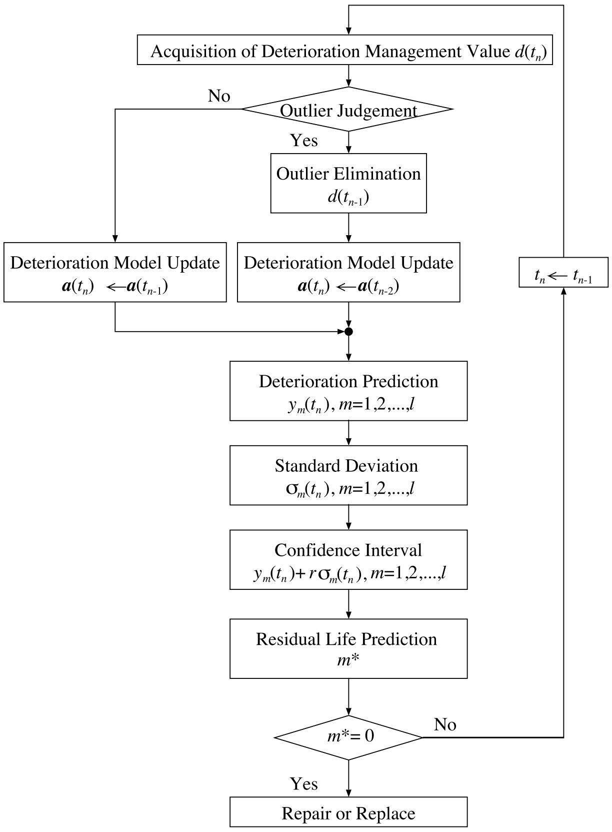



FIGURE 5. Detailed flowchart of deterioration management

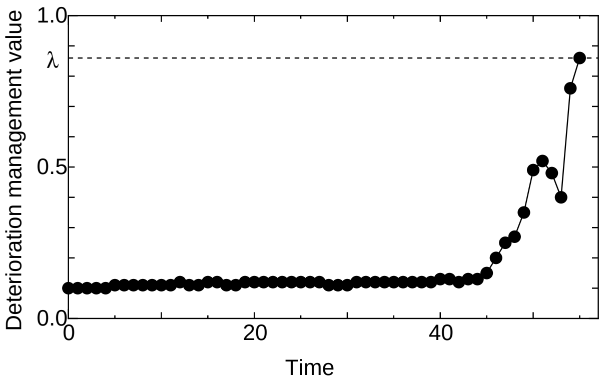



FIGURE 6. Vibration data of rotating equipment

(5) Predict the deterioration management values by using Equation (8).
(6) Evaluate the standard deviation by using Equations (10)-(14).
(7) Calculate the confidence interval by using Equation (9).
(8) Evaluate the residual life by using Equation (15).
(9) Judge the maintenance action if $m^* = 0$.

The main advantage of the proposed on-line residual life prediction is ease of introduction. Only an on-line measurement of the deterioration management value is required for the application of the proposed method. The predetermined parameters are confidence levels of the outlier judgement and a threshold value $\lambda$ for the residual life prediction.

## 4. **Application to Rotating Equipment.**

Table 1. Prediction results of the deterioration management values. Values in parentheses are upper bound of the confidence interval. The underlined values correspond to the excesses of the threshold value $\lambda = 0.86$.

| Time | Actual | 1 step ahead | 2 step ahead | 3 step ahead | 4 step ahead | 5 step ahead |
|---|---|---|---|---|---|---|
| 45 | 0.15 | 0.155(0.195) | 0.159(0.200) | 0.164(0.224) | 0.169(0.198) | 0.175(0.203) |
| 46 | 0.20 | 0.215(0.309) | 0.231(0.367) | 0.249(0.387) | 0.268(0.425) | 0.289(0.407) |
| 47 | 0.25 | 0.279(0.379) | 0.312(0.518) | 0.350(0.601) | 0.392(0.648) | 0.440(0.708) |
| 48 | 0.27 | 0.306(0.386) | 0.348(0.524) | 0.395(0.678) | 0.448(0.778) | 0.509(0.844) |
| 49 | 0.35 | 0.405(0.510) | 0.468(0.623) | 0.542(0.837) | 0.628($\underline{1.064}$) | 0.728($\underline{1.219}$) |
| 50 | 0.49 | 0.584(0.770) | 0.698($\underline{1.001}$) | 0.836($\underline{1.193}$) | 1.002($\underline{1.552}$) | 1.204($\underline{1.928}$) |
| 51 | 0.52 | 0.626(0.817) | 0.753($\underline{1.009}$) | 0.906($\underline{1.276}$) | 1.090($\underline{1.584}$) | 1.310($\underline{2.031}$) |
| 52 | 0.48 | 0.559($\underline{0.880}$) | 0.649($\underline{1.119}$) | 0.753($\underline{1.063}$) | 0.872($\underline{1.259}$) | 1.009($\underline{1.572}$) |
| 53 | Outlier | – (–) | – (–) | – (–) | – (–) | – (–) |
| 54 | 0.76 | 0.882($\underline{1.203}$) | 1.023($\underline{1.447}$) | 1.188($\underline{1.562}$) | 1.380($\underline{1.941}$) | 1.603($\underline{2.044}$) |

4.1. **Vibration diagnosis for rotating equipment.** The proposed method was applied to the rotating equipment in thermal power plants such as motors, pumps and fans [12]. Rotating equipment is inspected in operation (on-stream inspection) in order to retain functionality of the equipment. Faults of the rotating equipment generate unusual vibration signatures. In on-stream inspection, the condition of rotating equipment is commonly monitored by the systems that record vibration levels. The vibration-based diagnosis techniques used in nuclear power plants are summarized in [13]. In vibration inspection of rotating equipment, the acceleration of vibration is measured by using a special acceleration sensor. Hence, the acceleration of vibration of the rotating equipment is used for the deterioration management value. Figure 6 shows an example of the deterioration management values of rotating equipment in a thermal power plant.

4.2. **Deterioration model.** The mathematical model of the deterioration management value is given by

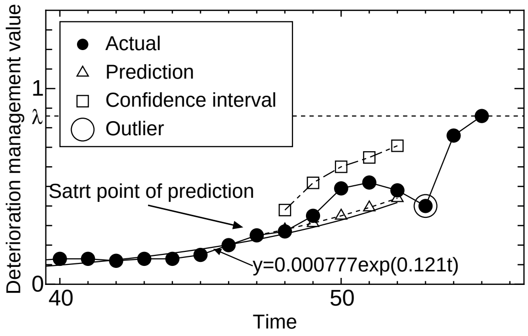
$$y(t_n) = c_2 \exp(c_1 t_n) \tag{16}$$

where $c_1$ and $c_2$ are model parameters. The constructed mathematical model is used to predict the deterioration management values of the rotating equipment. The $m$ step ahead prediction of the deterioration management value $y_m(t_n)$, $m = 1, \ldots, l$ where present time is $t_n$, is calculated by

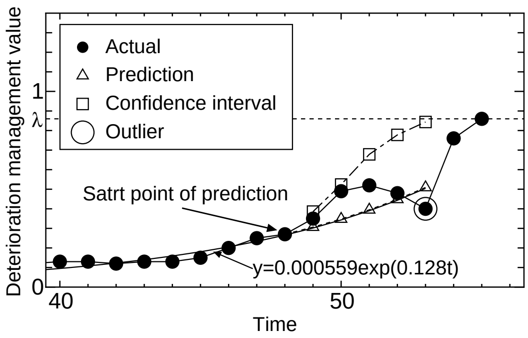
$$y_m(t_n) = d(t_n) + c_2(t_n) \left( \exp(c_1(t_n) t_{n+m}) - \exp(c_1(t_n) t_n) \right), \quad m = 1, \ldots, l. \tag{17}$$

4.3. **Results of deterioration prediction.** Figure 7 shows prediction results by using the constructed deterioration model where the weight was $\rho = 0.6$, the coefficient was $r = 3.0902$ (the confidence level for the confidence interval was 0.999), and the threshold value was $\lambda = 0.86$. Figure 7(a) shows prediction results at time 47, Figure 7(b) time 48 and Figure 7(c) time 49. As shown in Figure 7, the deterioration models represent the tendency of the deterioration and the deterioration models are well updated according to the deterioration progress. Moreover, for total prediction time, the actual deterioration management values are within the confidence intervals.

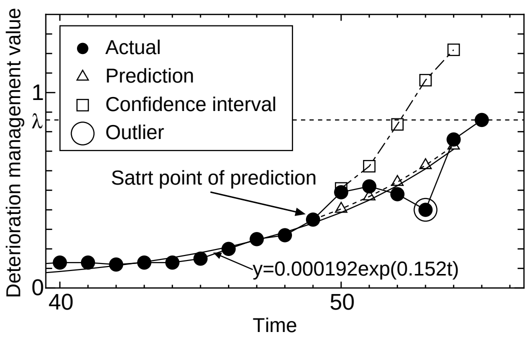
4.4. **Results of residual life prediction.** Table 1 shows multi-step ahead prediction results of the deterioration management values. In Table 1, upper values of the confidence interval are included in parentheses. When the upper bounds of the confidence interval exceeded the threshold value $\lambda = 0.86$, the residual life was estimated by using Equation




(a) Present time 47




(b) Present time 48




(c) Present time 49

FIGURE 7. Results of deterioration prediction and confidence intervals

(15). Figure 8 shows result of the residual life prediction. The residual life is appropriately estimated by using proposed method. The results show the effectiveness of the proposed residual life prediction method.

5. **Conclusion.** The on-line residual life prediction method was proposed and evaluated by applying rotating equipment in a thermal power plant. The on-line prediction result showed that predicted value was close to the actual deterioration management value, and the actual deterioration management value was within the upper bound of the confidence interval. The residual life was estimated by using proposed method, appropriately. Hence,

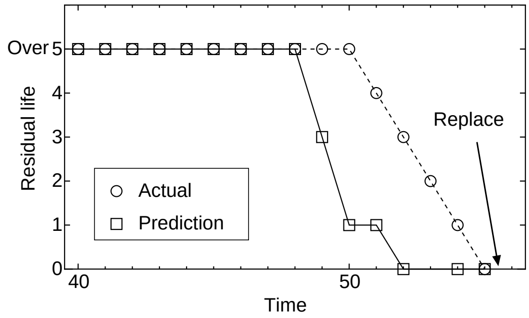



FIGURE 8. Prediction of residual life by using prediction of deterioration management value

repair time was correctly determined before the actual replace time. The results confirmed the effectiveness of the proposed residual life prediction method.

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