THE INFLUENCE OF DIAGNOSIS QUALITY ON THE ECONOMIC FEASIBILITY OF MAINTENANCE STRATEGIES FOR HV COMPONENTS

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Abstract: Condition based maintenance (CBM) strategies are widely applied in utility companies instead of time based maintenance (TBM), in order to reduce the maintenance costs. However, the extent of this reduction depends on the quality of the diagnosis. In this paper, we simulate the total lifecycle cost to operate 10000 cable connections for 100 years. Both time-based (i.e. TBM) and condition-based periodic maintenance (i.e. CBM) strategies are applied in the simulation. We assume that the failure probability vs. health condition index relationship satisfies a Weibull distribution estimated from laboratory test data. The diagnostic index is simulated through multiplying the health index h with a factor. This factor is assumed to follow a lognormal distribution with scale parameter η, and this η value indicates the error of diagnosis. From the simulation results, we learn that this diagnosis error indicator η and the cost of diagnosis have more significant influence than the failure loss on the decision between TBM and CBM. In addition, several methods to estimate the η value have been proposed. As a result, a generic process has been established for asset manager to judge whether a diagnosis method can be applied in CBM strategy and create economic profit.

1 INTRODUCTION

High voltage components are maintained preventively to reduce the risk of failure in their operation. Normally, two types of preventive maintenance strategies are applied on high voltage components, as [1] describes:

(1) Time Based Maintenance (TBM): an equipment maintenance strategy based on a fixed period of time, independent of the wear of the component at that time. Therefore, the strategy has just one parameter, the maintenance interval. In this paper we use TBM strategy to make maintenance for all the apparatus with optimal periodic interval.

(2) Condition Based Maintenance (CBM): an equipment maintenance strategy based on measuring the condition of equipment in order to choose appropriate action to avoid the failure in advance. Based on condition state, we use CBM strategy to make sequential maintenance for some part of the apparatus with periodic interval.

Condition based maintenance (CBM) strategies are widely applied in utility companies, which is commonly believed to provide more information about the health condition of components and achieves economic profits. However, the advantage of condition based maintenance relies on several conditions.

In this paper, a population of 10000 XLPE cable connections is installed at the initial year, and we simulate the total lifecycle cost (LCC) of the population within a decade similar as in [2]. Both time-based maintenance (i.e. TBM) and condition-based periodic maintenance (i.e. CBM) strategies are applied in the simulation.

2 INSTRUCTIONS OF SIMULATION MODELS AND PARAMETERS

2.1 The reliability model

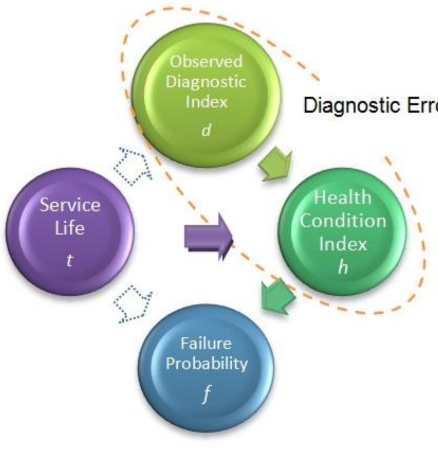

Figure 1: Relationship between four different events in the simulation model

The three most important variables in reliability of the apparatus are the service life t, the health condition index h and the failure probability f. In our previous research [2], the relationship between the maximum water tree length and failure probability of XLPE cable is investigated. In this paper, we use the water tree length, labelled with l, as the health condition index h. The relationship between l (or h), service life t and failure probability f are retrieved as follows and will be applied in our LCC calculations in Section 3.

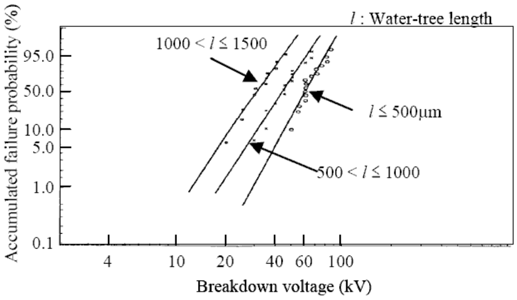

Figure 2: The Weibull distribution of breakdown voltage in the 6.6kV cables with different maximum water-tree length [3].

From the accelerating degradation experiment of water-tree in cables, the Weibull distributions of breakdown voltage in the cables with different maximum water-tree lengths (Figure 2) and the increase of the maximum water-tree lengths with time (Figure 3) can be obtained [3]. The accumulated failure probability F(l) under the rated voltage in the cable with the maximum water-tree length of l can be calculated From Figure 2. The average annual increase of the maximum water-tree length Δl can be calculated from Figure 3. Then the annual failure probability in the cable with the maximum water-tree length of l is expressed as

$$f(l) = F(l + \Delta l) - F(l) \tag{1}$$

Moreover, the variation of the distribution of the maximum water-tree length with time (i.e. the distribution of the maximum water-tree length $N_k(l)$ in the kth year) can be also obtained from Figure 3.

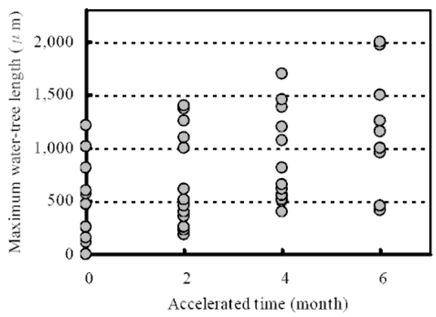

Figure 3: The increase of the maximum water-tree lengths with time in 6.6kV cables (The voltage frequency in the accelerating degradation was 1000Hz) [3].

Similarly to [4], we assume that a certain physical health condition index h, i.e. water tree length l, of power apparatus in the t th year follows logarithmic norm distribution as follows,

$$N_t(l) = \frac{1}{l\sqrt{2\pi\ \sigma(t)^2}} \exp[-\frac{(\ln l - \mu(t))^2}{2\sigma(t)^2}] \tag{2}$$

$$\mu(t) = \ln(l_0 + t\Delta l) \tag{3}$$

$$\sigma^2(t) = \sigma_0{}^2 + t\Delta\sigma \tag{4}$$

where l_0 is the initial water tree length, Δl is the average annual increment of the water tree length, σ_0 is the initial standard deviation, and $\Delta\sigma$ is the average annual increment of the variance.

We assume that the failure probability f vs. health condition index h (or l) relationship satisfies a Weibull distribution estimated from historical data [2-4].

$$f(l) = 1 - \exp(-(\frac{l}{A})^B) \tag{5}$$

where A is scale parameter and B is shape parameter. In the simulation, we use l_0=500, Δl=70, σ_0=0.618, A=9500 (μm) and B=4. These are the parameters achieved through laborartory accelerated aging tests on cables in [3]. The parameter A represents the characteristic length of failure, B represents the shape of the failure distribution, and σ_{d0} represents the initial difference in the ex factory quality of cables.

2.2 Diagnosis index and error

The length of water tree, the health condition index h in this paper, is a physical variable growing with service life and it influences the failure probability and, consequently, the remaining life. Unfortunately, it is a hidden variable which cannot be observed directly from field components due to the complexity of the failure causes and the harsh operating environment. Alternatively, diagnostic indices, such as partial discharges, are frequently observed as an indicator of health condition based on given knowledge rules. We label it as d in Figure 1.

As an observed value, the diagnostic index d does not equal to the health index h. We define the ratio between diagnostic index d and health condition index h as e:

$$d = h \cdot e \tag{6}$$

$$\sigma_{d0} = \sqrt{\sigma_0{}^2 + \eta^2} \tag{7}$$

Multiple factors can influence the e, such as reliability of sensors, precision of measurements, etc. In this paper, we only consider the insufficient volume of diagnostic data as the cause of diagnosis error. To be applied in CBM, diagnosis data are frequently analyzed statistically, in order to estimate a threshold value of diagnosis index. If the diagnosis index of a component is above this threshold, it is suggested to be replaced [5]. In statistics, the influence of data volume on the precision of this threshold is indicated with confidence bounds. And the confidence bounds on the threshold are recommended to be modelled with log-normal distribution [6]. Therefore, we assume that e has the below probability density function (pdf):

$$N(e) = \frac{1}{l\sqrt{2\pi\eta^2}} \exp[-\frac{(\ln Er)^2}{2\eta^2}] \quad (8)$$

This lognormal distribution has location parameter as 0, and the variance/scale parameter η. In this paper, this η is used to indicate the diagnosis error.

2.3 Costs of Maintenance Strategies

Three types of costs are included for each maintenance strategy: the failure loss (FL), replacement expenditure (RE) and diagnosis expenditure (DE). The difference between different types of repairs and partial replacements are neglected. Nor do we consider disposal. The FL includes multiple events such as damages, risks, loss of energy and unplanned replacements. Since a replacement is included, FL is always larger than RE. In the simulation, RE is always normalized to 1. FL is set to 20 according to the case of cables in [8] and DE is 0.05 according to [2].

ECOC is defined to be the total expected cost of one connection to serve one century. Thus, we get ECOC=LCC/10000. Logarithmic coordinates are used for comparability of ECOC value between CBM and TBM. The interest rate is assumed to be 5%.

$$ECOC = \sum_{i=0}^{100} \frac{FL * N_f(i) + RE * N_r(i) + DE * N_d(i)}{10000 \cdot (1+0.05)^i} \quad (9)$$

where N_f, N_r and N_d means respectively the number of 10000 components to fail, to be replaced and to be diagnosed in the *i* th year.

The total life-cycle cost LCC (i.e. the summation of the total failure loss TFL, the total replacement expense TRE and the total diagnosis expense TDE) can be also calculated by the method in [2]. The minimum total life-cycle cost corresponds to the optimized diagnosis parameters.

3 SIMULATION RESULTS

3.1 Quality of diagnosis

In many cases, the process of diagnosis helps to reduce redundant maintenance activities and corresponding costs. However, the extent of this reduction depends on the accuracy of the diagnosis and maintenance.

As the rise of parameter η, the dispersion of condition state within the population will be lager; further more increases the probability of faults in diagnosis and leading to the increase of ECOC.

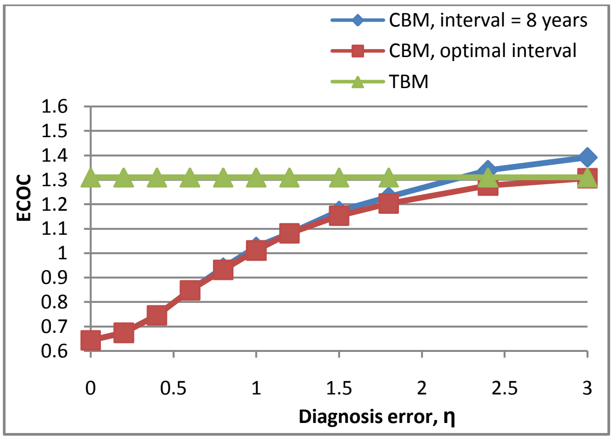

Figure 4: Relationship between ECOC and parameter η in TBM and CBM strategy at corresponding parameter A and B shown in Table 1 (σ_0=0.618, Δσ=0.01, FL=20, RE=1, DE=0.05).

We can see from Figure 4 that as the rise of η, indicating that the quality of diagnosis becomes poorer, the optimal ECOC of CBM increases. If the quality of diagnosis is better (i.e. when η is smaller), there will be the advantage of CBM over TBM. Influence of η is larger than the economic parameters.

If both interval and threshold are optimally selected for CBM, CBM will always keep its economic advantage. Larger diagnosis error will considerably reduce the economic advantage of the optimal CBM.

When η is large, the optimal interval CBM tend to converge to the optimal interval of TBM, and the optimal threshold of CBM is very low, i.e. always replace after diagnosis. In this situation, CBM has little difference from TBM. If diagnosis interval is not optimally selected, the CBM will even cost more than TBM with large η, as the “CBM, interval = 8 years” line shows in Figure 4.

In conclusion, maintenance strategy CBM is of advantage when the diagnostic quality is better.

3.2 Change on economic parameters

Three types of cost are included for different strategies: the failure loss (FL), replacement expenditure (RE) and diagnosis expenditure (DE). The difference between different type of repairs and partial replacements are neglected. Neither do we consider the disposal. The FL includes multiple damages, risks, loss of energy and unplanned repair. The RE includes both the expenses happened to replace the former cable connection with a new one and the market price of the new cable connection. In the simulation, we normalize RE to 1 and set FL=20 according to the case of cable in [8], and DE=0.05 according to [2].

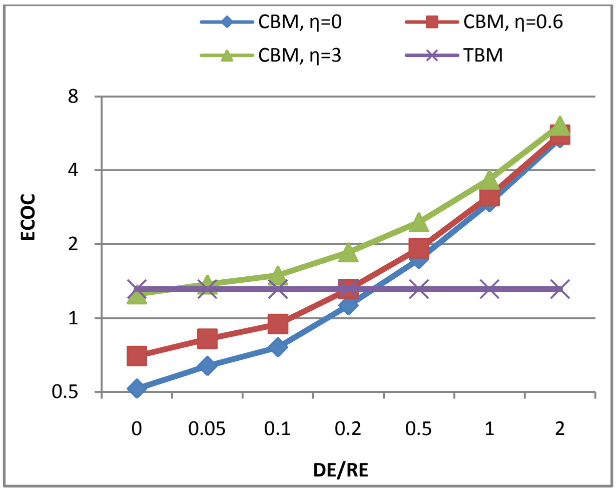

Figure 5: Relationship between ECOC and DE/RE in TBM and PDM strategy at different η ($\Delta\sigma$=0.01, σ_0 =0.618, FL=20).

By changing the relative value of the diagnosis expense (DE), we get the relationship of ECOC and the diagnosis expense at both TBM and CBM maintenance methods. The ECOC of TBM and CBM at different relative value of DE is shown in Figure 5. We fix diagnosis interval to 8 years and always choose the optimal threshold for each pair of DE and η.

Figure 5 shows that the selection between CBM and TBM depends on both diagnosis error and cost. When η=3, we will not choose CBM even if relative DE equals to zero. When relative DE is bigger than 0.2, we will not choose CBM even if η=0. The approximate values when ECOC of CBM equals to that of TBM is shown below: η=3, DE/RE=0; η=2.4, DE/RE=0.05; η=1.8 DE/RE =1; η=0.6, DE/RE =0.2

As the increase of relative DE, the advantage gained by maintenance method CBM over TBM becomes less. If quality of diagnosis is poor, TBM strategy is always preferred.

By changing the relative value of the failure lost (FL), we get the relationship of ECOC and the relative failure lost FL at both TBM and CBM maintenance methods, which is shown in Figure 6.

FL cannot change the choice between TBM and CBM. But large FL can enlarge the difference between CBM and TBM. If CBM do not choose optimal threshold, it will become worse than TBM. When the cost of failures is extreme cheap, there is no need to choose TBM/CBM, which means corrective strategy is enough.

In conclusion, if diagnosis is not accurate, the relative DE will influence the advantage CBM is of over TBM. However, the diagnosis quality itself will not change the relative advantage of CBM over TBM.

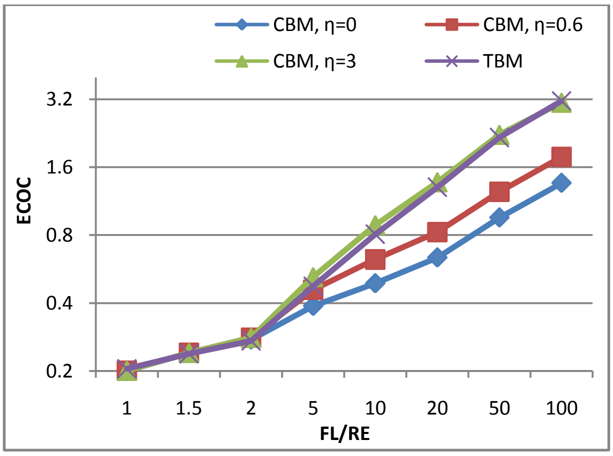

Figure 6: Relationship between ECOC and FL/RE in TBM and PDM strategy at different η ($\Delta\sigma$=0.01, σ_0 =0.618, DE=0.05).

3.3 Estimation of diagnosis error

Since h is not observable from field components, samples of e cannot be directly achieved through dividing d by h. In this situation, several methods can be chosen to estimate the diagnosis error indicator η.

Firstly, the distribution of d with service age t will be lognormal, because it is a multiply product of e and h, two lognormal distributed random variables. According to the attributes of lognormal distribution, η can be calculated from variance of d and h, when data of d and h of cables at a certain age is available:

$$\eta^2 = {\sigma_{d0}}^2 - {\sigma_0}^2 \tag{10}$$

$$\eta^2 = {\sigma_d}^2(t) - \sigma^2(t) \tag{11}$$

The parameter η of distribution of observed diagnostic index d is the same with that of health condition h and parameter σ_{d0} of distribution of observed diagnostic index d can be gained by following method:

$$\begin{aligned}
&\because d = l \cdot e,\ l \text{ and } e \text{ are independent, } l \text{ stands for } h \\
&l \sim \log N(\mu_0, \sigma_0^2) \text{ then } ln(l) \sim N(\mu_0, \sigma_0^2) \\
&e \sim \log N(0, \eta^2) \text{ then } ln(\mathrm{e}) \sim N(0, \eta^2) \\
&\Rightarrow \ln(l \cdot e) = ln(l) + ln(\mathrm{e}) \sim N(\mu_0, \sigma_0^2 + \eta^2) \\
&\Rightarrow l \cdot e \sim logN(\mu_0, \sigma_0^2 + \eta^2) \\
&\therefore d \sim logN(\mu_0, \sigma_0^2 + \eta^2)
\end{aligned}$$

Secondly, the distribution of d when failure occurs can be modelled with Weibull distribution. This is an approximation derived from the two facts: (1) the health condition index h is positively skewed, as Figure 3 shows; (2) the lognormal distributed e is also positively skewed. Consequently, fitting their multiply product d into a positively skewed Weibull distribution is suitable. When A=9500 and

B=4 for h, the A and B of d are related to η in the way shown in Figure 7. If data of d is available for some components before their failures, the Weibull parameters can be estimated for d, and η, can be further derived through comparing Weibull parameters of both h and d. The new parameters A and B for d are simulated by fitting new Weibull distribution based on the combination of one Lognormal distribution for η with original Weibull distribution of original parameters A and B. The diagnostic error increases the value of η in equations (7) correspondingly change the parameter A and B as well as the σ_{d0}.

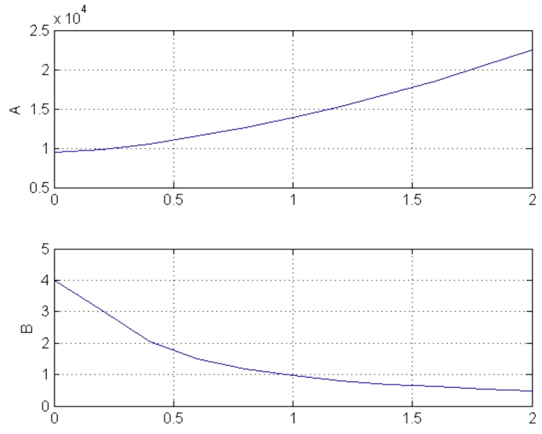

Figure 7: Effect of increasing diagnosis error η on the scale parameter A and shape parameter B of the Weibull failure probability.

The above two methods are sometimes difficult to be applied because the diagnosis data are not available before installation or exactly before failure. In this situation, the third method can be utilized. It uses the "probability of failure after diagnosis"[5].

Table 1: The probability of failure after diagnosis.

Diagnosis index \ Failure Probability	life>=5	Life<5
$d<d_t$=2800 State=Green	1-Pr	**Pr**
$d>=d_t$=2800 State=Red	(Pr_{II})	(1-Pr_{II})

For example, we take d_t as the boundary of "Green" and "Red" states. "Green" state is defined as a kind of condition state in which component has a good diagnosis index; while "Red" state is defined as a condition state in which component has a bad diagnosis index as shown in Table 1. "Green" state is set to keep operation until next diagnosis and "Red" state is set to replace immediately. If 1000 components are diagnosed and their d are below 2800, but 30 of them fails within 5 years after diagnosis, the η will be estimated as 0.5. We can only prove the probability of failure occurs in less than five years on conditions that the component is in Green state, i.e. Pr in Table 1. Accordingly, the probability (1-Pr) can be deduced. However, the probability of failure occurs in more than five years on conditions that the component is in Red state, i.e. Pr_{II}, can not be observed.

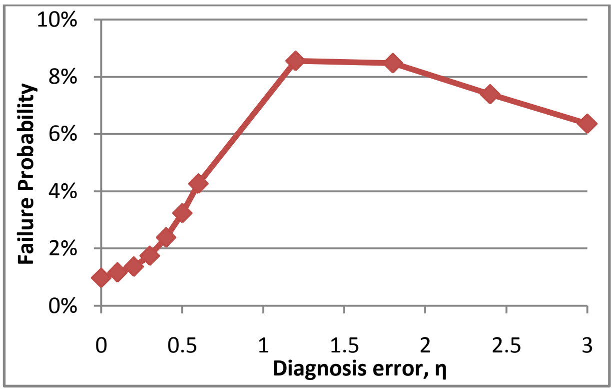

Figure 8: Probability of a component to fail within 5 years from the time when d_t=2800 is observed on it.

The Pr in Table 1 is the integral of three factors:

$$\Pr\left(t_{fail} - t < 5 \mid d_t = 2800\right) = \iint_{Er>0,\Delta h>1} \mathrm{P_1\,P_2\,P_3}\, de\Delta h \quad (12)$$

They are

(1) P_3: the conditional pdf of diagnosis error, given diagnosis index d_t:

$$\mathrm{P_3} = \mathrm{PDF}\left(h_t = e \cdot d_t \mid d_t = 2800\right) \quad (13)$$

(2) P_2: the conditional pdf of increase of health condition index Δh, given the diagnosis index d_t = 2800, and the health condition index is calculated from diagnosis error h_t.

$$\mathrm{P_2} = \mathrm{PDF}\left(h_{t+5} = h_t \Delta h \mid h_t, d_t = 2800\right) \quad (14)$$

(3) P_1: the conditional probability of failure, given h_t, Δh and d_t

$$\mathrm{P_1} = \Pr\left(h_{fail} > h_{t+5} \mid h_{fail} > h_t, \Delta h, h_t, d_t = 2800\right) \quad (15)$$

h_{fail} satisfies Weibull distribution as in equation(5), thus,

$$\Downarrow$$

$$\mathrm{P_1} = \frac{\mathrm{WblCDF}\left(h_{t+5}, A_h, B_h\right) - \mathrm{WblCDF}\left(h_t, A_h, B_h\right)}{1 - \mathrm{WblCDF}\left(h_t, A_h, B_h\right)} \quad (16)$$

where h_{t+5} follows lognormal distribution with (location parameter ln(2800+5*ΔI) and scale parameter square(σ^2+$\Delta\sigma$*5); h_t follows lognormal distribution with (location parameter ln(2800) and scale parameter σ as in equation(2). Thus Δh as the quotient between h_{t+5} and and h_t, satisfies a lognormal distribution with location parameter ln(2800+5*ΔI)-ln(2800) and scale parameter square(Δσ*50=0.01*5). We know from section 2.2 that Δ*l* =70 and Δσ=0.01.Consequently, P_2 equals to

$$P_2 = \text{lognCDF}\left(\Delta h, \ln(2800+5*70)-\ln(2800), \sqrt{0.01\times 5}\right) \quad (17)$$

As we know, *e* follows lognormal distribution with location parameter 0 and scale parameter η. d_t is a deterministic number 2800. Thus $h_t = d_t/e^*$ follows lognormal distribution with location parameter ln(2800) and scale parameter η.

$$P_3 = \text{lognCDF}\left(h_t, \ln(2800), \eta\right) \quad (18)$$

If replace d_t=2800 with other threshold values or “5 years” with other periods, the probability of failure can also be calculated

In addition, multi-factors can influence the aging process of apparatus which leads to unexpected failure probability. The dispersion of load and environment, such as soil condition, between apparatus are represented by the variance Δσ in equation (4). It proves in the former discussion that Δσ can not change the effect of diagnosis quality, but also influence the economic merit of CBM.

4 CONCLUSION

The calculation results show that diagnosis error indicator η, together with the diagnosis expenditure DE, makes decisions between TBM and CBM. FL does not change the choice between TBM and CBM. The quality of diagnosis and the variance of load and environment between apparatus will influence the economic merit of diagnosis strategy, CBM. The diagnosis may not always be more beneficial to the economic feasibility of maintenance rules, in which the quality of diagnosis plays an important role.

The η value can be estimated through several methods, namely (1) the distribution of diagnosis index at certain service life, (2) the distribution of diagnosis index before failure, (3) the rate of failure within 5 years after diagnosis. Asset manager can use these methods to judge diagnostic tools and maintenance strategies before their application.

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