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Optimal Maintenance Scheduling of Pumps in Thermal Power Stations through Reliability Analysis based on Few Data

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Abstract: In this paper we made a reliability analysis of power system pumps by using the dimensional reduction method which over comes the problem due to unavaialability of enpugh data in the actual systems under many different operational environments. Hence a resonable method was proposed to determine the optimum maintenance interval of given pump in thermal power stations. This analysis was based on an actual data set of pumps for over ten years in thermal power stations belonged to Kyushu Electric Power Company, Japan.

Keywords: Dimensional reduction method, few data, optimum maintenance, reliability, Future failure prediction

1. Introduction

Since a frequent preventive maintenance is a costly process, the determination of optimal solution has been a research interest to many researches. Raze [1] proposed a reliability prediction technique for mechanical equipments considering their components. Some other different planned maintenance procedures were proposed in literature [2] - [8]. The results of most researches are still circulated only among maintenance researches but are not applied by maintenance practitioners. We found several major factors for this unfortunate situation. Generally, the reliability analysis of mechanical equipments such as power system pumps are rather difficult and especially the involvement of many external as well as internal parameters together with less information lead to extreme difficulties in developing a valid prediction technique.

In this paper, to achieve the above needs with some modifications, we used the dimensional reduction technique [9] which we previously proposed. Dimensional reduction method can be used to analyze a small set of data subjected to many external and internal physical environments. We analyzed several hundred of actual pump data of 11 thermal power stations in Kyushu island, Japan and the effects of different operating environments on the failure rate are taken into account with the adaptation of dimensional reduction technique. With such a tool, maintenance engineers can identify pumps most likely to fail and the pump type or the size which contribute to its poor reliability. Since the failure data was available for only a small window of time relative to the average age of pump failure, the future pump failures were predicted using the assumption of Weibull distribution function. Thus, in general, for a profit oriented industry, the reliability or maintainability characteristics themselves do not give adequate measure, and should be combined with the costs for the final judgement. Hence we finally proposed a simple cost model to find the optimum maintenance interval of given pump.

2. Data Analysis through Dimensional Reduction Technique

2.1 Data acquisition and organization

Failure and population statistics of total 592 pumps in 11 thermal power stations of Kyushu Electric Company, Japan were analyzed. We made an effort to include the influence of all significant factors on the pump failure rate and examined the effects of varying operational environments and other physical parameters which were related to the failure rates of pumps. We distinguished seven most common and significant usage types of pumps in thermal power stations as feed water, steam, air, oil, combustion gas, sea water and condensed water. The pumps data were allocated into 3 size groups, five maintenance intervals (ΔT_j) each with 4,500 hrs width which have being used for the maintenance process so far and seven time to failures levels, each of 25,000 hrs width.

2.2 Dimensional reduction and TTF distribution of given pump

Since usage and size of pumps showed a close intercorrelation, those two parameters were combined to form the parameter X_m. According to the above classification, pumps failure data were allocated to form a three dimensional distribution with the parameters: operational usage and size X_m, average maintenance interval ΔT_j and time to failure T_k. The failure intensity of each level of the distribution $\lambda(X_m, \Delta T_j, T_k)$ can be ideally calculated as

$$\lambda(X_m, \Delta T_j, T_k) = \frac{N^f(X_m, \Delta T_j, T_k)}{N^t(X_m, \Delta T_j, T_k)} \qquad (1)$$

where X_m is the m^{th} level of operational usage and size, ΔT_j is the j^{th} level of average maintenance interval, T_k is the k^{th} level of time to failure of pumps, $N^f(X_m, \Delta T_j, T_k)$ and $N^t(X_m, \Delta T_j, T_k)$ are number of failure pumps and total number of pumps exposed to failure in $(X_m, \Delta T_j, T_k)$ level where m = 1 to 17, j = 1 to 5. and k = 1 to 7. Due to unavailability of enough data, most of the levels of the three dimensional distribution have zero elements and the direct calculation of failure intensity as in (1) is not appropriate. To solve this problem, we employed the dimensional reduction method with some modifications. In the dimensional reduction technique, the appropriate parameter selection of the primary distribution is very important and must be carefully done. Further any inter-correlations between parameters must be checked before they are selected as parameters in the distribution. The following sections give the details of dimensional reduction technique.

Table 1 The equivalent failure intensities with the parameter X_m (operational usage U and size S) where U_1 - feed water, U_2 - steam, U_3 - air, U_4 - oil, U_5 - combustion gas, U_6 - sea water and U_7 - condensed water

X_m	Usage	Size	$N^t(X_m)$ [pumps]	$N^f(X_m)$ [pumps]	$\lambda(X_m)$ [1]	$W(X_m)$ [1]
X_1	U_1	S_2	13	3	.230	1.00
X_2	U_1	S_3	73	10	.137	1.68
X_3	U_2	S_3	29	5	.172	1.33
X_4	U_3	S_1	33	1	.030	7.62
X_5	U_3	S_2	8	1	.125	1.85
X_6	U_3	S_3	35	3	.086	2.69
X_7	U_4	S_1	32	2	.062	3.69
X_8	U_4	S_2	25	1	.040	5.77
X_9	U_4	S_3	8	-	-	-
X_{10}	U_5	S_2	23	1	.043	5.31
X_{11}	U_5	S_3	34	1	.029	7.85
X_{12}	U_6	S_1	101	2	.019	11.65
X_{13}	U_6	S_2	11	-	-	-
X_{14}	U_6	S_3	14	-	-	-
X_{15}	U_7	S_1	51	1	.019	11.77
X_{16}	U_7	S_2	97	1	.010	22.40
X_{17}	U_7	S_3	6	-	-	-

2.2.1. Reduction to a 2 dimensional distribution

Failure intensity of each X_m level, $\lambda(X_m)$ was calculated as

$$\lambda(X_m) = \frac{N^f(X_m)}{N^t(X_m)} \tag{2}$$

where $N^f(X_m)$ and $N^t(X_m)$ are number of failures and total number of pumps exposed to failure in X_m level (see Table 1). Selecting the level X_1 as the base level for the parameter X_m, the weighting factors which are necessary for the dimensional reduction process were calculated for each X_m level ($W(X_m)$) as

$$W(X_m) = \frac{\lambda(X_1)}{\lambda(X_m)} \tag{3}$$

Table 1 shows the values of $\lambda(X_m)$ and $W(X_m)$. Failure data in each X_m level was transferred to X_1 level and equivalent number of failure pumps of each $(\Delta T_j, T_k)$ was calculated with respect to X_1 level as

$$N^f(\Delta T_j, T_k/X_1) = \sum_{m=1}^{17} N^f(X_m, \Delta T_j, T_k) W(X_m) \tag{4}$$

and the total number of pumps exposed to failure at $(\Delta T_j, T_k)$ level was given by

$$N^t(\Delta T_j, T_k) = \sum_{m=1}^{17} N^t(X_m, \Delta T_j, T_k) \tag{5}$$

According to the equations (4) and (5), with the elimination of parameter X_m, three dimensional distribution was reduced to a two dimensional distribution. Failure intensity at any level of two dimensional distribution was written as

$$\lambda(\Delta T_j, T_k/X_1) = \frac{N^f(\Delta T_j, T_k/X_1)}{N^t(\Delta T_j, T_k)} \tag{6}$$

In the dimensional reduction process, the actual raw data was used without loss of generality and only teh failure data were subjected to the dimensional reduction.

2.2.2. Reduction to one dimensional distribution

In order to reduce the dimension of the distribution to one dimensional distribution, the two dimensional distribution formed in the above section was further reduced

Table 2 The equivalent failure intensities with ΔT_j (average maintenance interval

ΔT_j	$N^t(\Delta T_j)$ [pumps]	$N^f(\Delta T_j)$ [pumps]	$N^f(\Delta T_j/X_1)$ [pumps]	$\lambda(\Delta T_j/X_1)$ [1]	$W(\Delta T_j)$ [1]
ΔT_1	111	3	4.37	.039	1.000
ΔT_2	218	13	36.94	.169	.233
ΔT_3	126	11	48.52	.385	.102
ΔT_4	65	4	25.08	.386	.102
ΔT_5	72	1	3.69	.051	.772

by selecting the parameter ΔT_1. Equivalent number of failure pumps of any ΔT_j level with respect to X_1 level of two dimensional distribution is

$$N^f(\Delta T_j/X_1) = \sum_{k=1}^{7} N^f(\Delta T_j, T_k/X_1) \tag{7}$$

and the total number of pumps exposed to failure at any ΔT_j level is

$$N^t(\Delta T_j) = \sum_{k=1}^{7} N^t(\Delta T_j, T_k) \tag{8}$$

The equivalent failure intensity of ΔT_j level is

$$\lambda(\Delta T_j/X_1) = \frac{N^f(\Delta T_j/X_1)}{N^t(\Delta T_j)} \tag{9}$$

where $N^t(\Delta T_j)$ is the total number of pumps exposed to failure in the ΔT_j level. Weighting factors of each ΔT_j level was calculated with respect to ΔT_1 level ($W(\Delta T_j)$).

$$W(\Delta T_j) = \frac{\lambda(\Delta T_1/X_1)}{\lambda(\Delta T_j/X_1)} \tag{10}$$

Table 2 shows the values of $\lambda(\Delta T_j/X_1)$ and $W(\Delta T_j)$.

Finally, three dimensional distribution was reduced to one dimensional distribution by calculating the equivalent failure intensity of T_k level with respect to selected base levels X_1 and ΔT_1 as

$$N^f(T_k/X_1, \Delta T_1) = \sum_{j=1}^{5} N^f(\Delta T_j, T_k/X_1) W(\Delta T_j) \tag{11}$$

and equivalent failure intensity of each T_k level with respect to $(X_1, \Delta T_1)$

$$\lambda(T_k/X_1, \Delta T_1) = \frac{N^f(T_k/X_1, \Delta T_1)}{N^t(T_k)} \tag{12}$$

where $N^t(T_k)$ is the total number of pumps exposed to failure in T_k. Table 3 shows the value of $\lambda(T_k/X_1, \Delta T_1)$.

2.2.3. Determination of failure intensity at any level

By following the above procedure, the initial three dimensional distribution was reduced to obtain the equiv-

Table 3 Equivalent failure intensities with T_k (time to failure) and cumulative intensities of T_k - $F(T_k)$

T_k [hrs]	$N^f(T_k)$ [pumps]	$N^f(T_k/X_1\Delta T_1)$ [pumps]	$\lambda(T_k/X_1, \Delta T_1)$ [1]	$F(T_k)$ [1]
T_1	6	5.62	.009	.009
T_2	4	4.68	.010	.019
T_3	8	2.79	.008	.027
T_4	4	4.40	.021	.048
T_5	5	4.71	.037	.086
T_6	4	2.37	.034	.119
T_7	1	1.19	.020	.139

alent failure intensity of any T_k level with respect to X_1 and ΔT_1. The actual failure intensity for given $(X_m, \Delta T_j, T_k)$, $\lambda(X_m, \Delta T_j, T_k)$ can be calculated by using the dimensional expansion as

$$\lambda(X_m, \Delta T_j, T_k) = \frac{\lambda(T_k/X_1, \Delta T_1)}{W(X_m)W(\Delta T_j)} \qquad (13)$$

Since the values of $W(X_m)$, $W(\Delta T_j)$ and $\lambda(T_k/X_1, \Delta T_1)$ are already known in (3), (10) and (12) respectively, the necessary calculations can be done to find the actual failure intensities of any given level of the distribution.

3. Prediction of future failures

Since the failure data are available only for a small window compared to the average age of actual pumps, it is needed to determine the pump failures for the remaining time period. Since the Weibull functions with different parameter values could cover a wide range of distribution shapes, it was selected to obtain adequate fit over the entire time frame. Hence the future failures of pumps were extrapolated.

3.1 Assumption of Weibull TTF distribution

TTF of pumps were assumed to follow a two parameter Weibull distribution with parameters σ and β as

$$f(T_k) = \frac{\beta T_k^{\beta-1}}{\sigma^\beta} \exp - \left(\frac{T_k}{\sigma}\right)^\beta \qquad (14)$$

where σ and β are scale parameter and shape parameter of the Weibull distribution respectively and the cumulative Weibull function becomes

$$F(T_k) = 1 - \exp(-(T_k/\sigma)^\beta) \qquad (15)$$

Since the actual TTF data exists only for $T_k < T_7$,

$$\int_0^{T_7} f(T_k)dT_k = \sum histogram \qquad (16)$$

For the range $T_k > T_7$, TTF intensities were extrapolated to satisfy the requirement

$$\int_0^{\infty} f(T_k)dT_k = 1 \qquad (17)$$

The Weibull parameters σ and β of corrseponding distributions were determined from the presently available data set by rearranging the equation (15) as

$$\ln\ln(\frac{1}{1 - F(T_k)}) = \beta\ln(T_k) - \beta\ln\sigma \qquad (18)$$

By using plots of $\ln\ln(1/1 - F(T_k))$ against $\ln(T_k)$ for each ΔT_j with each X_m level, the corresponding Weibull parameters were obtained. As an example, we selected feed water medium size pumps (X_1 level) and failure intensities of T_k of pumps for the maintanence interval ΔT_1 was replaced by Weibull distribution function with corresponding Weibull parameters. Fig. 1 shows the currently available TTF intensity data (in bars) and the Weibull curve that was used to extrapolate the remaining pump failures in feed water pumps with medium size (X_1 level). Similary Weibull parameters for each ΔT_j level was obtained. Table 4 shows the parameters of the Weibull distributions of X_1 level for each ΔT_j. Following the same procedure, the all Weibull distributions of X_2 to X_{17} were calculated for each ΔT_j.

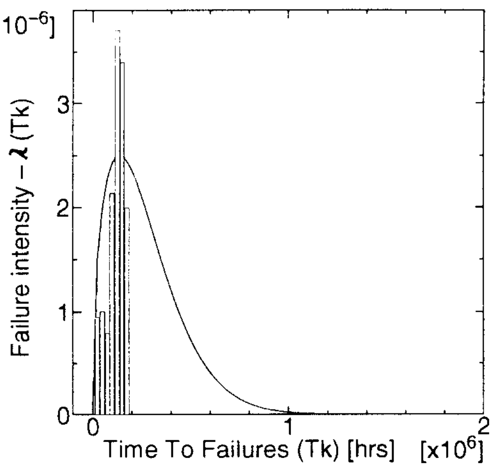

Fig. 1 Extrapolation of future failures by Weibull distribution for $(X_1, \Delta T_1)$ level

Table 4 The values of Weibull parameters with different maintanence intervals ΔT_j for X_1 level (feed water U_1 -medium size S_2)

ΔT_j	σ	β	$MTTF$ 10^5 [hrs]	$1/MTTF$ 10^{-6} [hrs^{-1}]
ΔT_1	2.96	1.57	2.64	3.70
ΔT_2	2.15	1.63	1.93	5.17
ΔT_3	1.00	1.97	0.88	11.26
ΔT_4	1.00	1.97	0.88	11.31
ΔT_5	0.47	1.82	0.43	23.24

3.2 Calculation of MTTF for given maintenance interval

The mean time to failure ($MTTF$) of the pumps for each maintenance interval ΔT_j was found by using corresponding weibull parameters as

$$MTTF = \sigma\Gamma((1+\beta)/\beta) \qquad (19)$$

where Γ shows the gamma function and will be given as

$$\Gamma(\alpha) = \int_0^{\infty} p^{\alpha-1}e^{-p}dp \qquad (20)$$

Since the values of Weibull parameters σ and β were already found for each maintanence interval ΔT_j, $MTTF$ of all maintanence intervals were calculated as in the equation (19) for X_1 level and tabulated in Table 4.

4. Cost consideration for determination of optimum maintenance interval

The above results in Fig. 2 shows that the frequent maintenance decreases the chance of failure of pumps

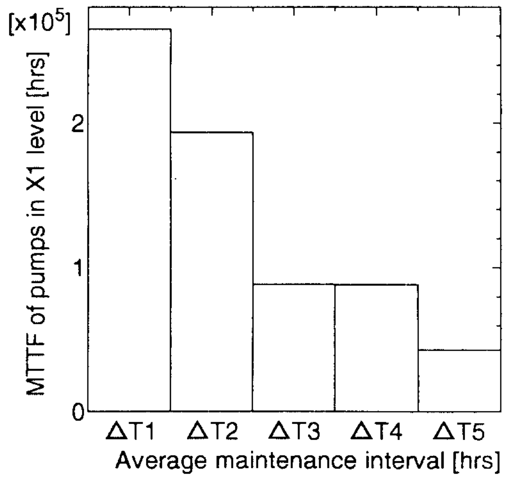

Fig. 2 Actual MTTF variation with average maintenance interval for X_1 level

Table 5 Total expected cost with different maintanence intervals for X_1 level (feed water U_1 -medium size S_2). The optimum maintenance interval which corresponds to minimum total expected cost, is ΔT_2 (4,500-9000 hrs).

ΔT_j	C_C	$C_p/\Delta T_j$	$C_f/MTTF$	C_T
ΔT_1	100	13.2	7.5	120.7
ΔT_2	100	6.7	10.3	117.0
ΔT_3	100	4.4	22.5	126.9
ΔT_4	100	3.3	22.6	125.9
ΔT_5	100	2.6	46.5	149.1

and increases the reliability. In a profit oriented organization, the provision of higher reliability is not enough and the overall cost must be considered for the optimal solution. With this in mind, we discussed a cost model which considers the pump cost including installation cost, failure cost and maintenance cost.

4.1 Construction of cost model

The decision problem is to find the optimal preventive maintenance time such that the expected system maintenance cost per unit of operation time is minimized. If the maintenance interval of a pump was assumed to be a constant through out the life time, the total expected cost of a pump per unit time (C_T) for given maintenance interval ΔT_j can be calculated as the addition of pump cost per unit time, pump maintenance cost and pump failure cost.

The total expected cost per unit time C_T can be written as

$$C_T = C_p + C_m/\Delta T_j + C_f/MTTF \tag{21}$$

where C_p is the exepected cost of a pump per unit time, C_m is the average cost of a maintenance and C_f is the average cost of a failure. If the values of C_p, C_m, C_f and $MTTF$ are known the value of optimum maintenance interval can be found as the value of ΔT_j which corresponds to the minimum total expected cost (C_T). It can be seen that the shape of the cost curves for each type of pump has a minumum which guaranties the existance of an optimal solution.

4.2 Illustration of results

In order to demonstrate the characteristics of the preventive maintenance scheduling model, the overall expected cost function C_T against the average maintenance interval ΔT_j are calculated. As an example, X_1 level was selected and the variation of total expected cost of a pump with the average maintenance interval ΔT_j is tabulated in Table 5. For the illustration of the results, the cost factors in (21) were assumed as follows: $C_p = 100$, $C_m = 10{,}000$ and $C_f = 2{,}000{,}000$. The above cost factors are not exact values in the power station that we analyzed data. The optimal maintenance interval was selected as the one with the minimum overall expected cost. According to the analysis, the optimum service interval of X_1 level (feed water U_1 - medium size S_2) is ΔT_2 (4,500-9,000 hrs). Although we showed minimums for overall cost in the above example, the exact values will be varied according to the values of cost factors in the model. This results shows the validity of the model and will give an idea of how to select the optimum maintenance interval.

5. Discussion

1. Analysis of small set of data: Due to unavailability of enough data and involvement of many parameters, it has been found some gap between the reliability theory and actual practice. In our attempt to analyze such data, we employed the dimensional reduction method with modifications. The technique used in this paper is proved to be applicable with appropriate selection of parameters, to any kind of such environments.
2. Future failure extrapolation: In most cases, the failure data of actual systems represents only a small time period relative to the actual life time. Under a such situation, an extrapolation of future failures are necessary for any reliability process. In this analysis we extrapolated the future failures of the pumps by using a distribution function of weibull from the present failures.
3. Consideration of a constant maintenance intervals: If the system ages the post-maintenance failure rate drops to some newer value, the successive maintenance interval must be treated as a decreasing one. But the failure rate of the actual pumps in thermal power stations were relatively small and to be considered as a constant through out their operation. Hence, in this paper we treated this problem by considering a constant maintenance interval through out the total age of operation of pumps.

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