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Gas Turbine Risk Assessment Based on Different Repair Assumptions

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Abstract: Currently throughout the world, gas turbine (power generation system) is used for fulfilling energy needs. Beside its abundant usage, it has high risk due to its unexpected failure nature. Thus, to mitigate the risk of gas turbine unexpected failure, risk assessment is important to be carried out. In this study, risk assessment is used to estimate the probability and magnitude of risk due to the unexpected system failures by considering different repair assumptions for gas turbine system. In order to measure the risk for different repair assumptions, the probability of failure and consequences are required. The probability of failure estimated using parametric Recurrent Data Analysis (RDA) approach while the consequences of failure analyzed based on reported data. The results indicated that minimal repair assumption leads to minimum risk compared to perfect and imperfect repair assumptions. Based on the results, it is concluded that the maintenance team need to follow minimal repair in order to minimize the expected cost of failure.

Key words: Gas turbine, risk assessment, recurrent data analysis

INTRODUCTION

Gas turbine is a repairable mechanical system which can produce huge quantity of energy based on its capacity (Yang and Hong, 2011). During the last 40 years, the usage of gas turbine has increased throughout the world in different sectors, especially in power plants (Boyce, 2011). In power generation plants, gas turbine mostly remain in continuous operation to fulfill the required demand. In ordered to meet the stated requirement, the gas turbine should have high operational reliability and low downtime. Like other repairable systems, in power generation system, risk is unavoidable. However, it can be mitigated using appropriate risk assessment method for lowering failure frequency, by selecting appropriate repair assumption. Generally there are two main repair assumptions, either “as good as new” or “as bad as old” but in reality the equipment lies somewhere in between these two conditions which is called as imperfect repair or “better than old but worse than new” (Doyen, 2005). The first two extreme assumptions for the repair work were discussed by many researchers, however, are found not much practicable. These assumptions are less accurate compared to the imperfect maintenance assumption, because the failure nature of the repairable system depends much on the repair history of system (Lindqvist, 2006; Majid and Nasir, 2011). Therefore, in order to evaluate the failure probability of repairable system, in this case gas turbine, it is necessary to consider the repair effectiveness.

Many researches have been conducted to assess the risk of the gas turbine system. Moon *et al.* (2009) have done the risk assessment of gas turbine propulsion design to know the impact of various design aspects and their related risks to recommend the best design. Goel *et al.* (2008) have carried out risk assessment of gas turbine blades failures and performed statistical approaches for the fault diagnosis to minimize gas turbine failures. Roemer and Kacprzynski (2001) have performed the risk assessment of gas turbine machinery health by integrated use of advance diagnostics and prognostics technologies. These modern technologies can be used for low and high level turbo machinery to minimize the overall life cycle cost. Forsberg (2008) has evaluated the risk of failure of gas turbine discs under thermal and centrifugal loads.

In many studies on risk assessment of gas turbine systems, the effect of repair effectiveness which has major influence on the failure probability of the system, was not yet integrated. Thus, in this study, risk is evaluated considering various types of repair assumptions for the gas turbine system. To measure the risk for various repair assumptions, probability of failure estimated with parametric Recurrent Data Analysis (RDA) approach. This approach is able to predict failures of gas turbine system for all three types of repair assumptions. Beside failure probability, consequences of failure calculated based on reported data. Only economic consequences of failure are considered in this study.

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MATERIALS AND METHODS

In this study, three step procedure was carried out to analyze the risk of the gas turbine system. In the first step, the failure probability was analyzed using RDA technique, secondly failure consequences were determined and thirdly risk quantification was done.

Failure probability: In this step, the probability of system failure is defined using parametric RDA approach. This approach is based on GRP model which provides a way to determine the recurrence rate of system failures over time by taking into account the effect of repair on succeeding failures. Moreover, RDA approach uses Power Law Model to estimate the failure probability. Model parameters are calculated based on the method of Maximum Likelihood Estimation (MLE). Power law intensity function can be written as Eq. 1 (Crow, 1990):

$$\lambda\ (t) = \lambda\beta t^{\beta-1} \tag{1}$$

where, λ represents the scale parameter, β represents the shape parameter and t is the system age. The value of each parameter is greater than zero. Hence, mean value of power law function is expressed as Eq. 2:

$$E\ (N(t)) = \lambda t^{\beta},\ t>0 \tag{2}$$

where, λ and β parameters can be estimated using Maximum Likelihood (ML) method by Eq. 3 and 4, (Mettas and Zhao, 2005):

$$ß = \frac{n}{\sum_{i=1}^{n-1} \ln(\frac{t_n}{t_i})} \tag{3}$$

$$\lambda = \frac{n}{t_n^{\beta}} \tag{4}$$

where, n shows nth number of failure and t_i shows successive times to failure with $0<t_1<t_2<\ldots<t_n$. The value of λ and β parameters may remain constant or may change by different repair assumptions which are perfect repair, imperfect repair and minimal repair. After each type of repair the age of the system varies. The age of the system can be defined based on the Kajima GRP Type-I and GRP TYPE-II models (Mettas and Zhao, 2005).

Let assume a repairable system, where some maintenance actions are taken after each failure to improve system performance, let:

- t_1, t_2, t_3... t_n are the successive times for system failures
- x_1, x_2, x_3...x_n denote the time between failures for system
- q be the maintenance effectiveness factor
- If value of q = 1 its minimal repair, q = 0 perfect repair and if 0<q<1 it will be considered imperfect repair

Now GRP Type-I model assumes that the ith repair can remove accumulated age since ith failure only. It can only reduce the additional age x_i to qx_i. It can be represented by Eq. 5:

$$v_i = v_{i-1} + qx_i = qt_1 \tag{5}$$

where, v_i expresses the virtual age of repairable system after the ith repair.

GRP Type-II model, assumes that up to the ith failure virtual age has been accumulated to $v_{i-1}+x_i$. In this type, ith repair will remove the cumulative damage to system due to current and all previous failures, by reducing the virtual age to $q(v_{i-1}+x_i)$. It can be estimated using Eq. 6:

$$v_i = q(v_{i-1} + x_i) = q^i x_1 + q^{i-1} x_2 + \ldots + x_1 \tag{6}$$

Failure consequence analysis: The consequence analysis is the quantification process for the of the effect failure occurrence (Krishnasamy *et al*., 2005). In case of power plant failure consequences include repair cost, loss of opportunity due to the down time and maximum demand charge due to hook up to main utility during plant failure. Whenever system cannot fulfill required electricity capacity due to failure, it needs to use alternative electric supply source which will impose maximum demand charge each time. The plant also has to pay, for the amount of electricity consumed during that system down time. Then failure consequences can be given as Eq. 7 (Nasir *et al*., 2012):

$$\begin{aligned}\text{Consequences of failure} = {} & \text{Repair cost+Loss opportunity cost+} \\ & \text{Amount of electricity by alternate} \\ & \text{source cost+Maximum demand charge cost}\end{aligned} \tag{7}$$

Repair cost estimation: Maintenance repair cost is based on the cost of spare parts, labor cost etc. Cost of repair will be calculated using Eq. 8 (Nasir *et al*., 2012):

$$Cr = R_c \sum_{i=1}^{n} N_1 \tag{8}$$

Now Cr is the total repair cost in MYR, N_i is the expected number of the failures per year and R_c is the cost of repair per failure.

Loss opportunity cost estimation: This cost can be estimated using Eq. 9 (Marquez, 2007):

$$\text{Loss opportunity cost} = C_E K \times \sum_{i=1}^{n} DT_i \tag{9}$$

In Eq. 9, C_E is the cost of electricity in MYR, K is the amount of electricity plant supposed to produce in kW, DT_i is the downtime in hours.

Cost incurred due to alternative supply: This cost can be expressed as in Eq. 10, it shows the costs incurred due to using alternative electricity supply source (Ray, 2006):

$$\text{Cost incurred due to alternative supply} = C_E L \times \sum_{i=1}^{n} DT_i \tag{10}$$

where, L is the amount of the electricity supplied from other source.

Maximum demand charge cost: This cost can be expressed as in Eq. 11, it shows maximum demand charge cost:

$$E \times (\text{max: Demand in kW}) \tag{11}$$

where, E is the fixed cost in MYR kW h^{-1} of maximum demand.

Risk assessment: It is systematic analysis to quantify probability and magnitude of losses due to system failure. Mathematically, it can be represented as Eq. 12 (Modarres, 2006):

$$R = \sum_{i=1}^{n} N_i \times c_1 \tag{12}$$

where, R is the expected risk value and N_i is expected number of failures per year and c_i shows the consequences per failure.

RESULTS AND DISCUSSION

Case study: To demonstrate the applicability of the model, a gas turbine system operating at campus Gas District Cooling (GDC) plant which has capacity of 4.2 MW is considered. One year gas turbine performance data is used to estimate the failure probability. The data was collected during the peak hours between 8 am to 5 pm for weekdays. The limit for minimum production capacity is set based on the work done by Muhammad *et al*. (2009) on similar configured system. Whenever system performance is below 1500 kW limit, it is considered as failure of system as shown in Fig. 1. Further, time to failure (TTF) and cumulative time to failure of the gas turbine are shown in Table 1.

Selection of the model: From Kajima virtual age models GRP Type-I and GRP TYPE-II selection were done based on MLE technique. Greater the likelihood value of the model, best will be the statistical fit for the given data. Based on this assumption GRP Type-I was selected, results of the estimated parameters are depicted in Table 2.

Estimation of parameters for GRP Type-I model at different q value: After selecting GRP Type-I, the parameter estimation was done by setting q = 0, 0<q<1 and q = 1. As discussed in methodology when the value of q is 0, the system follows perfect repair whereas if q is 1, the system repair is minimal. If q is between 0 and 1, the system follows imperfect repair. Based on these assumptions, the λ and β values were estimated and are shown in Table 3. The results of the Table 3 shows β value is more than 1 when q = 0 but it decreases when

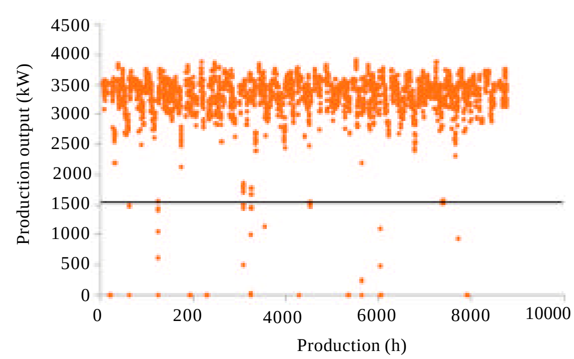

Fig. 1: Failure occurrence during peak demand

Table 1: TTF for gas turbine

Failures No.	TTF (h)	Cumulative TTF (h)
1	27	27
2	297	324
3	603	927
4	63	990
5	396	1386
6	315	1701
7	495	2196
8	162	2358
9	99	2457
10	738	3195
11	81	3276

Table 2: Model selection based on MLE value

Parameters and LK value	Kijima Type-I
β	1.339436
λ	0.000389
q	0
LK value	-67.337122

Table 3: GRP Type-I parameters at different q values

Parameters	q = 0	0<q<1	q = 1
β	1.339436	0.861152	0.824511
λ	0.000389	0.008786	0.012635

Table 4: Risk estimation for perfect repair

Year	Expected cumulative No. of failures	Consequences per failure (MYR)	Expected risk value (MYR)
1	9.856	169200	1667600
2	20.13	169200	3405900
3	30.28	169200	5123300
4	40.66	169200	6879600
5	50.80	169200	8595300
6	61.10	169200	10338100

Table 5: Risk estimation for imperfect repair

Year	Expected cumulative No. of failures	Consequences per failure (MYR)	Expected risk value (MYR)
1	9.940	169200	1681800
2	18.112	169200	3064500
3	26.192	169200	4431600
4	33.618	169200	5688100
5	40.824	169200	6907400
6	47.822	169200	8091400

Table 6: Risk estimation for minimal repair

Year	Expected cumulative No. of failures	Consequences per failure (MYR)	Expected risk value (MYR)
1	11.119	169200	1881300
2	17.709	169200	2996300
3	24.739	169200	4185800
4	31.3621	169200	5306400
5	37.697	169200	6378300
6	43.812	169200	7412900

value of 0<q<1 and q = 1. The value of λ increases consequently from q = 0-1 through 0<q<1.

Estimation of expected number of failures: Knowing the expected failure frequency is essential to evaluate the risk of failure. The six years cumulative expected number of failures for different repair assumptions is indicated in Fig. 2-4. All three repair assumptions were having different failure trends for the gas turbine system. Figure 2 shows the expected cumulative number of failures when the system follows perfect repair. At the end of year one, there is a possibility to have 9.856 failures. This number of the failures remains almost constant for each consecutive year, because this is perfect repair assumption. The cumulative number of failures for perfect repair at the end of year six, is estimated to be 61.1, also shown in Table 4.

Figure 3 shows the failure numbers for imperfect repair, at the end of year one, the number of failures estimated is 9.94. The failure frequency for this repair assumption is lower as compared to perfect repair assumption. Because at the end of year six, total cumulative number of expected failures estimated is to be 47.822, also depicted in Table 5.

Figure 4 shows the cumulative number of failures for minimal repair and it is observed that the expected number of failures at the end of year one, is 11.11. But failure frequency decreases during each consecutive year. At the end of year six, cumulative number of failure estimated is 43.812. Hence, the gas turbine has approximately constant frequency of failure and high cost, if it is repaired by perfect repair assumption for each time.

Risk quantification: The downtime was extracted from the available system failure data and the labor cost rates and other production related costs were assumed based on reported data. The consequences per failure were estimated using Eq. 7 are approximately 1, 69,200 MYR for each failure.

Risk quantification for six years was done for different repair assumption using Eq. 12 and the results are depicted in Table 4-6. The total risk value for perfect repair is about 10338100 MYR while the risk for imperfect repair was about 8091400 MYR and for minimal repair was 7412900 MYR. The gas turbine incurs high cost value when it adapts perfect repair which is 10338100 MYR. The results revealed that minimal repair could minimize the cost of failure of the gas turbine system by 28.29 and 8.38% compared to perfect repair and imperfect repair, respectively.

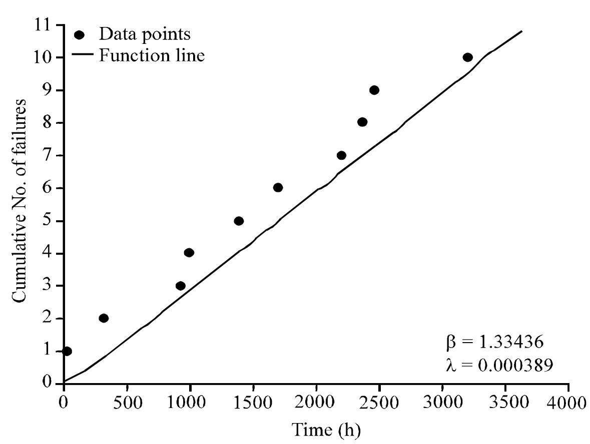

Fig. 2: Expected No. of failures for perfect repair

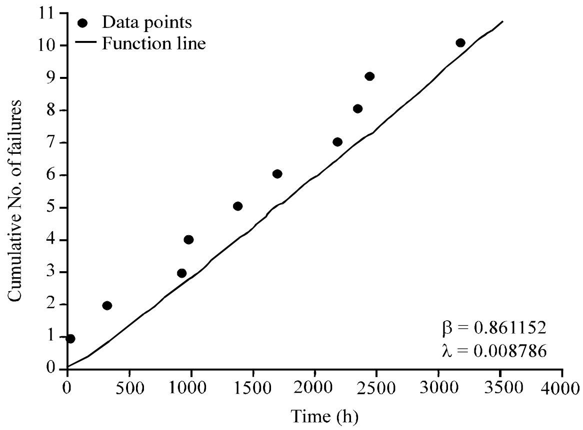

Fig. 3: Expected No. of failures for imperfect repair

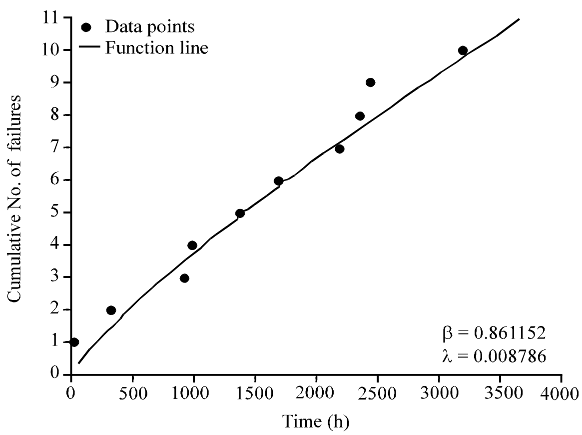

Fig. 4: Expected No. of failures for minimal repair

CONCLUSION

In this study, risk assessment was carried out of gas turbine system considering different repair assumptions. For the analysis, failure probability and consequences of the failure were required. For failure probability, parametric RDA method was used which is more advance and effective method in predicting the failure frequency of gas turbine system for all three types of repair assumptions which are perfect repair, minimal repair and imperfect repair. The consequences of the failure calculated based on the reported data.

Gas turbine system operating at GDC plant is taken as case study to illustrate the use of model for gas turbine risk assessment. The results revealed that minimal repair could minimize the cost of failure for gas turbine by 28.29 and 8.38% compared to perfect repair and imperfect repair, respectively. Thus, minimal repair assumption would mitigate the risk of high maintenance cost and failure of the gas turbine. Hence, maintenance team need to adopt minimal repair for gas turbine maintenance.

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