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Modelling of System Failures in Gas Turbine Engines on Offshore Platforms

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Abstract: The system reliability of gas turbine engines on offshore platforms, maintained (i.e. repaired) upon process failures, is considered in this study. A set of condition monitoring (CM) data (i.e. failure events) of a selected gas turbine engine is considered, where the system maintenance actions with minimum repair conditions (i.e. that should not disturb the failure rate intensity) are assumed. A nonhomogeneous Poisson process is used to model the age dependent reliability conditions of a gas turbine engine and maximum likelihood estimation (MLE) for calculating the same model parameters is implemented. Finally, a summary on the system behavior under failure intensity, mission reliability and mean time between failures (MTBF) is also presented in this study.

Keywords: System reliability, failure rates, failure intensity, gas turbine engines, maximum likelihood estimation, nonhomogeneous Poisson process.

1. INTRODUCTION

Industrial power plants are life critical systems in offshore platforms and their operational behavior (i.e. failure rates) can be used to encounter their diagnostic and prognostic challenges. Since these power plants play a crucial operational role in the oil and gas industry, this study proposes to understand the system failure behavior under aging conditions and that can also be used to formulate optimal maintenance policies. In general, these power plants consist of various engine-power configurations (i.e. reciprocating engine, gas-turbines, etc.) to satisfy the power requirements of offshore platforms. These engines are operating under harsh ocean environmental conditions; therefore condition monitoring (CM) and conditions based maintenance (CBM) applications should be implemented to overcome the respective degradation conditions.

This study is based on an offshore power plant with four industrial gas turbine engines/generators and that is located in a floating production, storage and offloading (FPSO) unit. The offshore platform is located in Campos Basin in Rio de Janeiro and an additional study on the same platform is done in (Machado *et al.,* 2014). These FPSO units have often been used by the offshore industry to receive, to process and to store the hydrocarbons produced from nearby offshore platforms and sub-sea production systems. This system consists of 4 turbo-generators consisting of aero-derivative gas turbine engine with normal capacity of 25000 (kW) coupled with electric generators with normal capacity of 28750 (kVA). The required grid load of the offshore platform approximately 35-45 (MW) and each generator is rated for approximately 12-15 (MW). Therefore, at least 3 generators in the isochronous mode should be operated to satisfy the requirements of the offshore platform.

In general, gas turbines have been used under open cycle and combined-cycle application in various power plants. In combined cycle approach, the exhaust gas temperature can be used to run steam generators as an energy recovery approach. As the power plant consists of several gas turbine engines, the system reliability measures on a selected gas turbine engine is considered in this study. Therefore, the system failure intensity of a gas turbine has been considered to model the overall power plant behavior. Furthermore, it is important to identify the system failure situations in these power plants ahead of time; therefore the optimal maintenance policy should be implemented to minimize the operational cost. That has been done by analyzing the CM data from the respective gas turbine engine.

2. SYSTEM RELIABILITY

Complex systems can often be repaired after failure events and those system failures can be modeled as stochastic processes. A system operational period (i.e. system age) that starts at $t=0$ and continues until $t=T$ with a number of failures $N(T)$ is considered in this model. Furthermore, these failure events are recovered by a same number of repairs with negligible time periods. The time periods for those failures from $t=0$ can be considered as $X_1, X_2, \ldots, X_N$. The $i-th$ successive operational period between two failures events can be considered as $X_i - X_{i-1}$ where $i=1,2,\ldots,N$. These failure events are often been considered as an independent, identically distributed (IID) random variable that can be molded as a Poisson process (HPP) with the respective failure rate (λ). One should note that these repairable systems have often been modelled as Poisson process models and the inter-occurrence times (i.e. functioning time failures) in those events are independent events with exponential behavior, in which can be presented in system failure rates.

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However, the system failure rate with an increasing (i.e. deteriorating), constant (i.e. neither deteriorating nor improving) or decreasing (i.e. improving) trends can be observed by the Laplace trend test (LTT). Hence, the LTT test statistics can be written as (Kim et al., 2004):

$$U_L = \left. \frac{\sum_{i=1}^{n} X_i}{N} - \frac{T}{2} \right/ T\sqrt{\frac{1}{12N}} \tag{1}$$

When the LTT value is greater than zero, the system has an increasing trend (i.e. decreasing reliability) and the Laplace trend test value is less than zero, the system has a decreasing trend (i.e. increasing reliability) can be concluded. This test statistics approximate a standard normal distribution, therefore the significant level of the results can also be observed from the standard normal table. Therefore, this test has been considered as the first step in this CM data analysis.

However, a Poisson process model with a constant failure rate (i.e. homogenous Poisson process) cannot capture the system reliability throughout its life cycle. Therefore, that has often been limited to a section of the system life cycle. Hence, the system operational considerations such as mission reliability, reliability growth or deterioration, and maintenance polices cannot be included in these models (i.e. constant failure rates). Therefore, a nonhomogeneous Poisson process for modelling of the system failure events in a gas turbine engine is also considered. One should note that the time intervals between two respective failures in a nonhomogeneous Poisson process cannot be IID, because the system age has effected on the system failure rate. Hence, the system failure rate intensity of a system can be written as (Crow, 1990):

$$\mu(t) = \lambda\beta t^{\beta-1} \tag{2}$$

where $\lambda > 0$ and $\beta > 0$ are system parameters and t is the age of the system. One should not that when $\beta < 1$, $\mu(t)$ is decreasing (i.e. the phase of infant mortality), when $\beta = 1$, $\mu(t)$ is a constant (i.e. the phase of useful life) and when $\beta > 1$, $\mu(t)$ is increasing (i.e. the phase of wear-out). It is assumed that the system has restored to its previous conditions after each failure with "minimal repair", where the intensity of the system failures has not been disturbed (Crow, 1975). Therefore, this behavior can also be described under the famous "bath-tub curve" for a system life cycle (Klutke *et al.,* 2003). Similarly, the power laws mean value function (i.e. the expected number of failures,) for a nonhomogeneous Poisson process with the failure intensity in (2), the expected number of failures for the same system during the system life time of $(t_{i-1} \quad t_i]$, can be written as:

$$\mathrm{E}[N(t_{i-1} \quad t_i) = n_i] = \int_{t_{i-1}}^{t_i} \mu(t)dt = \lambda t_i^{\beta} - \lambda t_{i-1}^{\beta} \tag{3}$$

where $N(t_{i-1} \quad t_i) = n_i$ is the number of failures that are experienced during the same system life time. One should note that (3) represents the expected number of failures (i.e. mean value) during the same system life time. Hence, the probability of encountering n_i failures during the same system life time can be written as:

$$\mathrm{P}[N(t_{i-1} \quad t_i) = n_i] = \frac{\mathrm{E}[N(t_{i-1} \quad t_i)]^{n_i} e^{-\mathrm{E}[N(t_{i-1} \quad t_i)]}}{n_i!} = \frac{\left(\lambda t_i^{\beta} - \lambda t_{i-1}^{\beta}\right)^{n_i} e^{-\left(\lambda t_i^{\beta} - \lambda t_{i-1}^{\beta}\right)}}{n_i!} \tag{4}$$

Therefore, the mission reliability (i.e. the probability that the system operational conditions that are satisfied without any failures) of the system for the same system life time can be written as:

$$R(t) = e^{-\int_{t_{i-1}}^{t_i} \mu(t)dt} = e^{-\int_{t_{i-1}}^{t_i} \lambda\beta T^{\beta-1}dt} = e^{-\left(\lambda t_i^{\beta} - \lambda t_{i-1}^{\beta}\right)} \tag{5}$$

However, to calculate the conditions derived in (3), (4) and (5), the parameters for the nonhomogeneous Poisson process model in (2) should be estimated. Hence, maximum likelihood estimation (MLE) is proposed to estimate those parameters and there are several optimal properties of MLE can be identified with respect to other parameter estimation methods (Myung, 2003). Considering the failure events in (4), the likelihood function can be written as (Smith and Oren, 1980):

$$\begin{aligned} L(\lambda, \beta) &= \prod_{i=1}^{N} \mathrm{P}(N(t_{i-1}, t_i) = n_i) = \prod_{i=1}^{N} \frac{\left(\lambda t_i^{\beta} - \lambda t_{i-1}^{\beta}\right)^{n_i} e^{-\left(\lambda t_i^{\beta} - \lambda t_{i-1}^{\beta}\right)}}{n_i!} \\ &= \prod_{i=1}^{N} e^{-\left(\lambda t_i^{\beta} - \lambda t_{i-1}^{\beta}\right)} \prod_{i=1}^{N} \frac{\left(\lambda t_i^{\beta} - \lambda t_{i-1}^{\beta}\right)^{n_i}}{n_i!} = e^{-\lambda T^{\beta}} \prod_{i=1}^{N} \frac{\left(\lambda t_i^{\beta} - \lambda t_{i-1}^{\beta}\right)^{n_i}}{n_i!} \end{aligned} \tag{6}$$

Considering (6), the log likelihood function can be written as:

$$\log L(\lambda, \beta) = -\lambda T^{\beta} + \sum_{i=1}^{N} n_i \left(\log\lambda + \log\left(t_i^{\beta} - t_{i-1}^{\beta}\right)\right) + \log n_i! \tag{7}$$

The partial derivatives of both parameters, λ and β, should be considered in (7) to calculate the maximum likelihood values for the respective parameters and that can be written as:

$$\begin{aligned} &\frac{\partial}{\partial\lambda} \log L(\lambda, \beta) = -T^{\beta} + \frac{1}{\lambda} \sum_{i=1}^{N} n_i = 0 \\ &\frac{\partial}{\partial\beta} \log L(\lambda, \beta) = -\lambda T^{\beta} \log T + \sum_{i=1}^{N} n_i \frac{\left(t_i^{\beta} \log t_i - t_{i-1}^{\beta} \log t_{i-1}\right)}{\left(t_i^{\beta} - t_{i-1}^{\beta}\right)} = 0 \end{aligned} \tag{8}$$

Hence, the maximum likelihood values of λ and β in (8) satisfy the following conditions:

$$\begin{aligned} &\hat{\lambda} = \frac{\sum_{i=1}^{N} n_i}{T^{\beta}} = \frac{N}{T^{\beta}} \\ &-\lambda T^{\beta} \log T + \sum_{i=1}^{N} n_i \frac{\left(t_i^{\beta} \log t_i - t_{i-1}^{\beta} \log t_{i-1}\right)}{\left(t_i^{\beta} - t_{i-1}^{\beta}\right)} = 0 \end{aligned} \tag{9}$$

One should note that (9) should be solved iteratively and that has a unique solution for the parameters of λ and β. However, the solution can calculate under time truncated and failure truncated situations. A situation with the observations that are truncated after a prefixed time for a respective number of failures (i.e. the number of failures is a random variable) is considered as time truncated. A situation with the observations that are truncated after a prefixed number of failures for a respective time interval (i.e. the time interval is a random variable) is considered as failure truncated. However, a time truncated situation with respect to the