Modelling Component Failure Rates Utilizing Sensor-Based Degradation Data

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Abstract: In the nuclear power industry, risk monitors are intended to provide a point-in-time estimate of the system risk given the current plant configuration. Current risk monitors are limited in that they do not take into account the *deteriorating* states of plant equipment. Current approaches to on-line risk monitors use probabilistic risk assessment (PRA) techniques, but the assessment is typically a snapshot in time. Living PRA models attempt to address limitations of traditional PRA models in a limited sense by including temporary changes in plant and system configurations. However, information on plant component health (a.k.a. level of degradation) are not considered. This often leaves risk monitors using living PRA models incapable of conducting evaluations with dynamic degradation scenarios evolving over time. There is a need to develop enabling approaches to enhance risk monitors to provide time- and condition-dependent risk by integrating traditional PRA models with condition monitoring and prognostic techniques.
This paper presents an exponential model for estimating the mean failure rate of components undergoing degradation, and Bayesian inference for updating the distribution of component failure rates. Such a degradation model is based on component performance data gathered over the service life and historical failures. The proposed model is demonstrated using component performance and failure data obtained for five motors subjected to accelerated degradation. The model provides a more realistic picture of the component risk and also forms an important prognostic tool capable of aiding risk-informed decision making.

Keywords: PRA, Dynamic PSA, Aging and Degradation.

1. INTRODUCTION

Current static probabilistic risk assessment (PRA) techniques prevalent in the nuclear industry are mainly based on event- and fault-tree analysis [1, 2]. The static PRA techniques formulate system- and plant-level risk scenarios based on basic event probabilities that model a system's or plant's response to component failures or initiating events and compute quantities ranging from probabilities of system failure to core damage frequencies. The event- and fault-tree-based PRA is commonly performed in the nuclear industry using PRA tools like Systems Analysis Programs for Hands-on Integrity Reliability Evaluation (SAPHIRE) [3] or the Computer Aided Fault Tree Analysis System (CAFTA) [4]. The risk levels of structures, systems, and components (SSCs) defined within existing PRA models are traditionally not updated as the SSCs age or as their performance degrades. The current risk assessment is typically a snapshot in time, and the information on plant component condition is often not considered. This limits current PRA models from conducting an evaluation of dynamic degradation scenarios.
The existing approaches of incorporating component aging and degradation in PRA include physics-based models that are suitable for degradation phenomena with existing physical models of degradation like corrosion and fracture [5], and logistic function-based approaches that assess the likelihood of a failure event given the degradation level [6]. This paper presents a novel failure-rate-based model of incorporating degradation of nuclear SSCs into an existing PRA model and associated risk monitor. Several existing approaches that quantify component degradation from measurement data are aimed at estimating remaining useful life (RUL), or at performing prognosis for condition based maintenance [7-9]. This work is specifically aimed at estimating the component failure rate, or probability of component failure, as a function of the component degradation.
The failure rates or probability of failure for components across the U.S. commercial nuclear power plants (NPPs) can be obtained from databases such as the U.S. Nuclear Regulatory Commission's Reactor Operational Database [10]. However there does not exist any database that can provide performance measurements taken over specific components operating under healthy or degraded states.

Therefore this work utilized the data from an extensive accelerated degradation experiment performed over twenty electrical motors [7].

2. COMPONENT DEGRADATION AND HAZARD RATE MODEL

The component failure rate λ modeled as a function of its performance measure is $\lambda = g(\boldsymbol{z})$ where $\boldsymbol{z} = (z_1, \dots, z_n)$ is the vector of n parameters measured for the component. In a NPP, mechanical and electrical components undergo rigorous periodic measurement of parameters like flow measurement, temperature, pressure, vibration, and current signal, along with technical log of historical maintenance, operating profiles etc., that can be used to estimate the performance measure $\boldsymbol{z}$ for the component at a specific point in time. In his seminal work on survival analysis, Cox [11] proposed an exponential variation of failure rate as a function of performance measure as

$$\lambda(\boldsymbol{z}) = \lambda_0 exp(\beta \boldsymbol{z}) \tag{1}$$

where λ_0 is the baseline hazard rate and β is an unknown parameter. Solving equation (1) entails knowing the value of the failure rate λ for at least two states of the component at known degradation states. Let $\boldsymbol{z} = \boldsymbol{z}_0$ be the performance measure of a healthy component, i.e. a component with no degradation. Let $\lambda = \lambda_0$ be the failure rate of a healthy component. Commonly, λ_0 is the failure rate of the component used in the traditional static PRA calculations. In this work, the failure rate is modeled using performance measures obtained from running motors until failure under accelerated degradation conditions. The failure rate lambda was obtained by using Bayesian inference with the failure data set. When described as a random variable for a population of components, the failure rate λ follows a Gamma (α, β) distribution, where α is the shape parameter and β is the rate parameter and the probability density function (PDF) of λ is

$$f(\lambda; \alpha, \beta) = \frac{\beta^{\alpha} \lambda^{\alpha-1} e^{-\beta\lambda}}{\Gamma(\alpha)}, \lambda > 0 \text{ and } \alpha, \beta > 0. \tag{2}$$

Consider a population of N_c initially healthy components with failure rate described by the Gamma distribution in equation (2). Let each of the N_c initially healthy components undergo degradation, culminating in failure of each component. Let the 'time to failure' for each of the N_c components be denoted by $t_1, t_2 \dots, t_{N_c}$, and assume the random variable t describing time to failure of the population follows an exponential distribution $t \sim Exp(\lambda)$. Then the PDF of time to failure is

$$f(t; \lambda) = \lambda e^{-\lambda t}. \tag{3}$$

The time to failure data $t_1, t_2 \dots, t_{N_c}$ can be used to update the PDF of failure rate λ by invoking Bayesian inference with prior distribution $f(\lambda; \alpha, \beta)$ from equation (2) and the likelihood $f(t; \lambda)$ in equation (3), the posterior distribution is then given by [12]

$$\begin{aligned} f(\lambda|t) &= \frac{\left(\beta + \sum_{i=1}^{N_c} t_i\right)^{\alpha+N_c} \lambda^{\alpha+N_c-1} e^{-\left(\beta+\sum_{i=1}^{N_c} t_i\right)\lambda}}{\Gamma(\alpha+N_c)} \\ &= Gamma\left(\alpha + N_c, \beta + \textstyle\sum_{i=1}^{N_c} t_i\right). \end{aligned} \tag{4}$$

The mean failure rate of degraded components is given by

$$\lambda_F = (\alpha + N_c) / \left(\beta + \textstyle\sum_{i=1}^{N_c} t_i\right). \tag{5}$$

The performance measure at time of failure be $\boldsymbol{z_F} = (z_1, \dots, z_n)$, for each of the failed components. Recalling the failure rate for healthy components as $\lambda = \lambda_0$ when $\boldsymbol{z} = \boldsymbol{z}_0$, and now $\lambda = \lambda_F$ when $\boldsymbol{z} = \boldsymbol{z}_F$ can be utilized for solving equation (1) for the failure rate modeled as a function of performance measure.

3. MOTOR TESTING AND DEGRADATION DATA

Ten 5-HP U.S. Electrical Motors/Emerson general-purpose industrial motors were chosen as low cost analogs to the high power induction motors found throughout industry [7]. The motors were run through a degradation cycle on a weekly basis. A cyclic thermal aging process, designed to induce accelerated insulation breakdown and corrosion within the motors, was applied to each of these three-phase, 3600 rpm motors. First, the motors were heated for three days in an oven. After the heating cycle, the motors were placed in a moisture testing bed with high humidity for further degradation. Then the motors were allowed to cool for a few hours before being placed in the second heating cycle for three additional days. After the second heating cycle, the motors were placed on a test bed and run for one hour. The accelerated aging plan has been adapted from a previous work and as suggested by IEEE Standard 117 (1974) [13, 14]. The IEEE Standard 117 also recommends that the motors undergo moisture testing as well as thermal degradation to better simulate normal operating conditions. In order to achieve the moisture testing, the motors were placed in a condensation chamber consisting of temperature-regulated coolant in a sealed container for a total of 48 hours at 100 % humidity. After a thermal aging cycle, each motor was mounted on a test bed, connected through an elastomeric coupling to a generator, and instrumented with a data collection system to collect various key signals.

Fifteen different parameters were measured for each motor as follows: Input Current and Voltage for each of the three phases (1-6), Phase angle (7), Vibration horizontal and vertical (8-9), Acoustic amplitude (10), Tachometer data (11), Speed in rpm (12), Output current and voltage (13-14), and temperature (15) [7]. Because the purpose of this paper is to demonstrate the methodology of modeling component failure rate as a function of performance measure, only one quantity was used to keep the methodology simple to demonstrate. The acoustic data was found to be most significant in capturing the degradation of motors, therefore the following results and discussion are based on acoustic data used for modeling the evolution of failure rate of motors. Also, of the twenty motors in the experiment, a subset of five motors (# 2, 3, 4, 5, and 6) that demonstrated the strongest acoustic signals was used.

4. RESULTS AND DISCUSSION

The failure rates for healthy components λ_0 can be obtained from NUREG/CR-6928 published by the U.S. NRC [10]. This report lists the industry average of failure rates and probability of failure of mechanical and electrical components commonly used in the US commercial NPPs. Since NUREG/CR-6928 does not list three phase motors as distinct component, $\lambda_0 = 4.54 \times 10^{-6}/hr$ and $\alpha = 1.655$ was chosen, which are values close to those describing failure rates of motor-driven pumps.

The time to failure for the five motors obtained from the experiment are 150, 131, 156, 133, 151 hours respectively. Plugging in equation (4) the failure times t_i, $i = 1,\ldots,5$, and $N_c = 5$, the posterior distribution of failure rate is obtained. Figure 1 shows the prior and the posterior distribution of λ. The posterior mean indicates failure rate of the degraded motors when the five motors failed, i.e. λ_F.

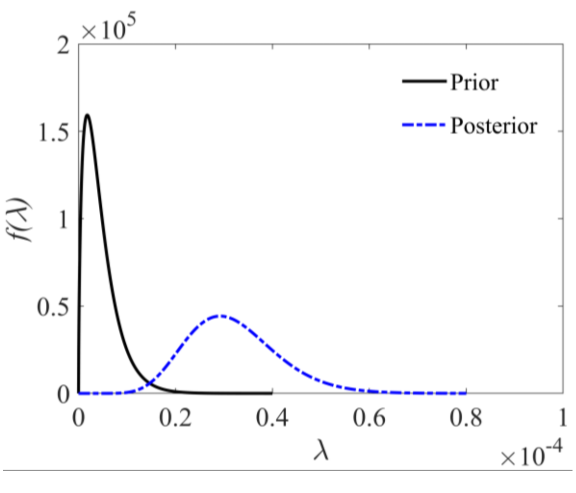

Figure 1. The prior Gamma distribution of failure rate of the motors, and the posterior distribution obtained from equation (4).

The component performance measure z is obtained from the raw acoustic data in the following manner. During the experiment the acoustic data was measured at 17,000 points over a period of 2 seconds during each test. In this work, the root mean square (RMS) value of each signal is obtained indicating one measurement value for one test. Figure 2 (a) and (b) show the acoustic signal measured, and the RMS value for

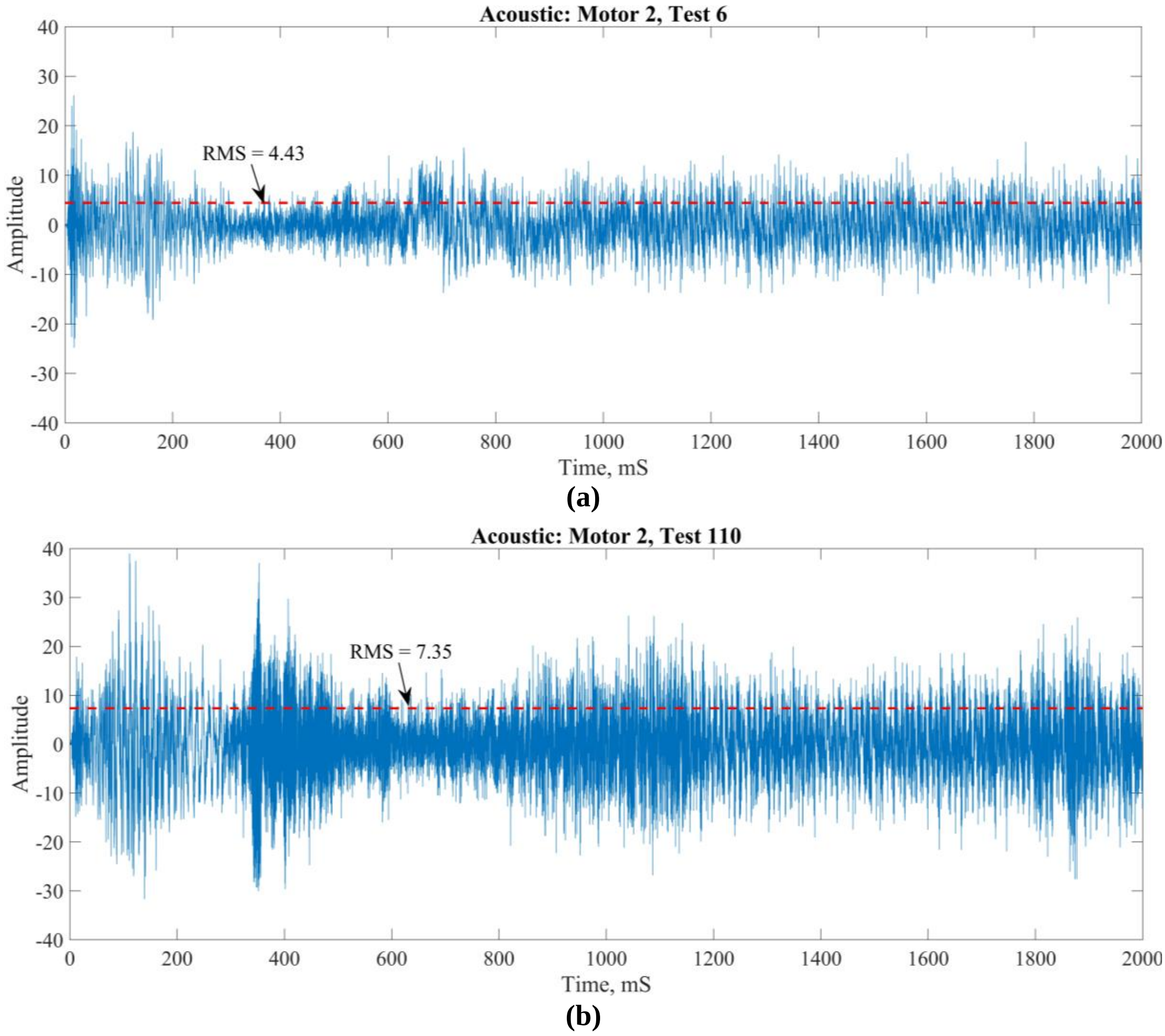

Figure 2. The raw acoustic amplitude and its RMS value measured on motor 2 for two tests in (a) healthy and (b) degraded state of the motor.

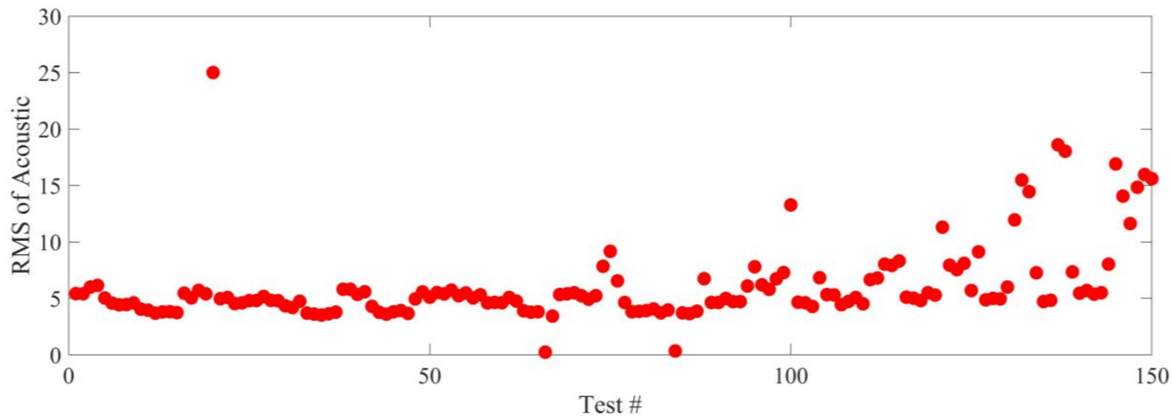

Figure 3. RMS value measured on motor 2 for each test up to the failure of the motor.

two tests, 6 and 110, indicating healthy and degraded states respectively of motor 2. There is a clear increase in the RMS value when the motor is in a degraded state. Figure 3 shows the RMS value of acoustic data of motor 2 across the 150 tests that the motor lasted. In order to successfully detect the distinct outliers, and to clearly identify a trend in degradation, moving variance of the RMS values was calculated. Figure 4 (a) shows the raw and the moving variance of the RMS values of the acoustic data

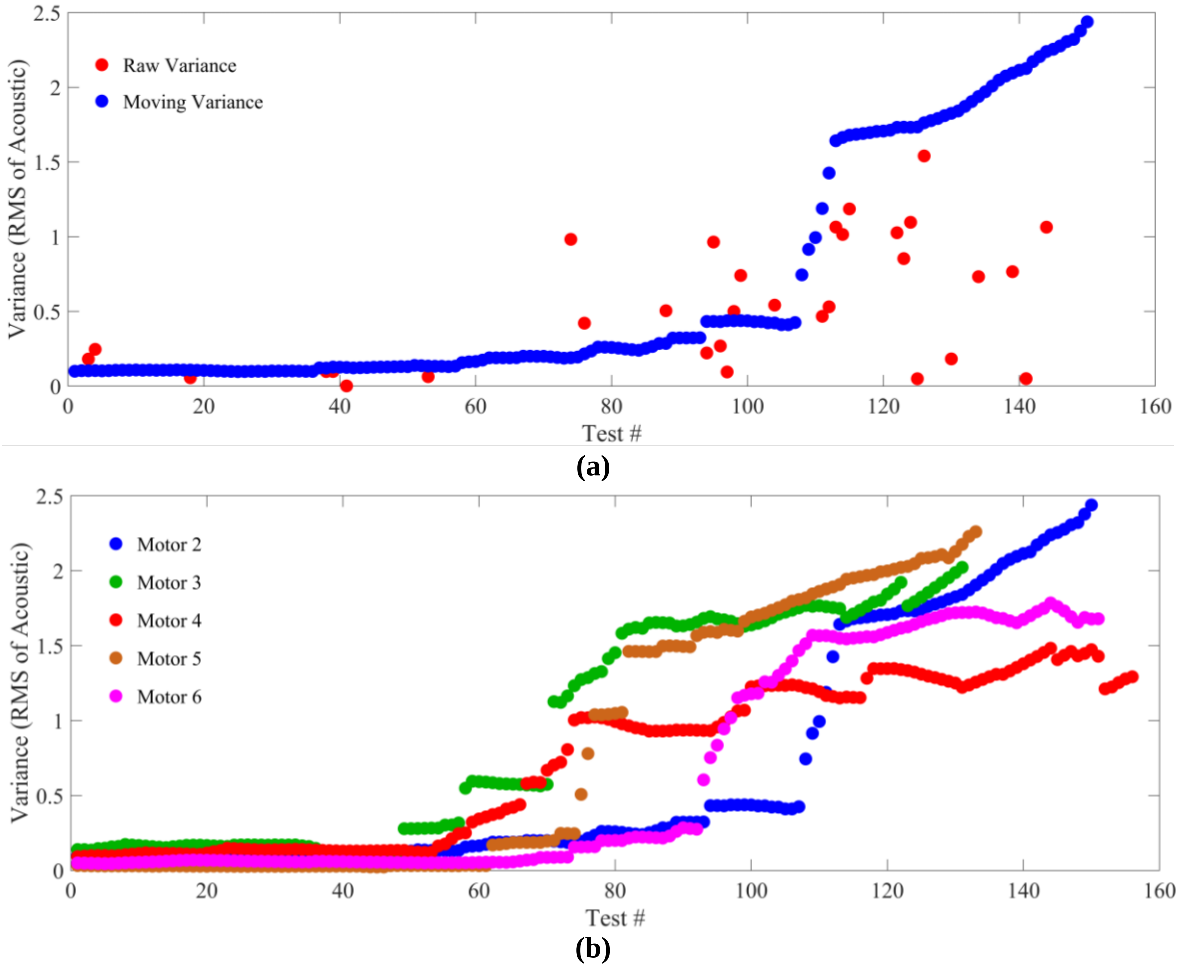

Figure 4. (a) Raw variance and moving variance of motor 2. (b) Moving variance of the five motors.

for motor 2. The window size for calculating the moving variance was chosen as half the length of the data, i.e. $t_i/2$ for each motor. It is clear that the moving variance successfully illustrates a trend of degradation leading up to the time to failure. Therefore the performance measure z for modeling the failure rate of motors is chosen as the value of moving variance of the RMS value of acoustic amplitude (Figure 4 (b)).

The moving variance results in a clear trend of motor degradation states. The initial healthy state is indicated by constant values of the variance, followed by a rapid transition phase indicating a degraded state, and then reaching a maximum value of indicative of impending failure. On observing the initial constant variance values it was determined that the start of motor degradation phase can be indicated by the variance value exceeding 0.2, i.e. the motor failure rate are assumed to stay constant at $\lambda = \lambda_0$ when $z < 0.2$. The relation between the failure rate and the performance measure is defined as

$$\lambda(z) = \begin{cases} \lambda_0 & z < z_{th}, \\ \lambda_0 exp(\beta z) & z \geq z_{th}. \end{cases} \tag{6}$$

where z_{th} is the threshold beyond which component starts to undergo degradation, which in case of moving variance is determined empirically as $z_{th} = 0.2$. The unknown parameter β in equation (6) can be obtained by fitting the model between the two points (z_{th}, λ_0) and (z_F, λ_F), where z_F is the measurement obtained when the component failed and λ_F is calculated from equation (5). Figure 5 illustrates the fitted exponential model along with the 95% confidence interval. Such a model can readily provide an estimate of mean failure rate of a component under degraded state when its performance measure is available.

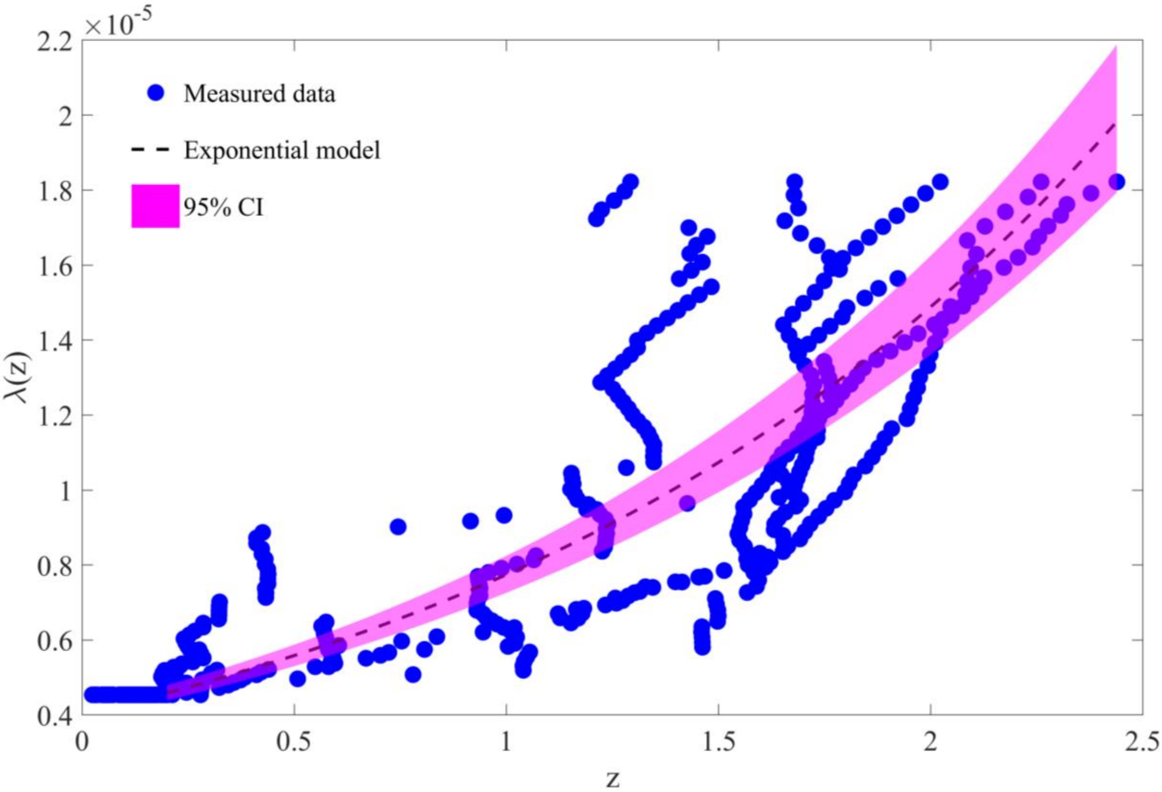

Figure 5. The fitted exponential model of failure rate (equation (6)) with the data points.

4. CONCLUSION AND FUTURE WORK

A framework to model failure rates of components as a function of their performance measure is demonstrated. An exponential model is proposed and is modeled using the failure rate of component in a healthy state and the failure rate obtained in a failed state from Bayesian inference. The model is demonstrated using experimental data obtained from an accelerated degradation test performed over five motors. The failure rate evolution is modeled as a function of moving variance of the RMS value of acoustic amplitude. The model can be used for estimating the mean failure rate of components under degradation. Future work entails incorporating multivariate covariates into the exponential model of failure rate, and performing rigorous validation of the proposed model.

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