Reliability Analysis of Flow Meters with Multiple Failure Modes in the Process Industry

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Key Words: flow meters; multiple failure modes; nonhomogeneous Poisson process; left-truncated; right-censored

SUMMARY

Reliability analysis of flow meters is an important issue for process industry companies because of the need to ensure the production quality and operational safety. In practice, field data for flow meters failure process can have complicated structure due to multiple failure modes arising from different electro-mechanical parts. Besides, incomplete records generally exist. For example, the installation date is usually not available, making the failure data left-truncated. There also exist right-censored cases since many units are still in service when the data are analyzed. In this paper, we use a nonhomogeneous Poisson process model with power-law intensity functions to address multiple failure modes for field data with both left-truncated and right-censored cases. We apply the maximum likelihood method to estimate the model parameters. In order to address the statistical uncertainty, random weighted likelihood bootstrap procedure is used to estimate the standard errors and confidence intervals of the parameters. Real-world flow meters failure data from a process industry company are used in the case study. Estimated intensity functions and estimation of mean time to failure are obtained and show that the parametric model can reasonably fit the failure data well.

1 INTRODUCTION

Measurement of volumetric or mass flow rate of a liquid or a gas, is commonly used in many industrial processes (e.g., material manufacturing) as a critical indicator. Continuously accurate flow measurements are important to establish baseline material usage, improve product quality, and ensure safe operational environments. In particular, Coriolis mass flow metering has been considered as the most accurate of the commonly-used industrial flow measurement technology since its introduction in the mid 1980s [1]. Coriolis meters offer several advantages, such as better accuracy and ability to measure both mass flow and density, so that they are widely accepted in process industry companies [2]. However, Coriolis meters are typically expensive because of (1) the high manufacturing quality requirements and (2) the relatively larger size since flow meters above three or four inches become exceedingly large and commensurately expensive [3]. Unexpected failures of flow meters will cause a shutdown of the production process, resulting in a large amount of economic losses (i.e., downtime cost) including direct costs (e.g., raw material, energy, labor, profit lost) as well as hidden costs (e.g., decreased company competitiveness and reputation, customer dissatisfaction), and may also cause safety problems for the operational environments. Therefore, reliability analysis of flow meters is of great importance for process industry companies. It is critical for these companies to have in-depth understanding of the flow meters failure mechanism and accurate estimation of mean time to failure so that they can make better informed decisions on maintenance scheduling and spare parts provisioning.

In practice, reliability analysis of flow meters is challenging for the following reasons. First, during the service life of a flow meter, multiple types of failures can occur and require different types of repairs. For example, failures of electronics, loosing coils and cables, and blocked tubes can make a flow meter unable to function, but it can be repaired by replacement of electronics, tightening the coils and cables, and cleaning tubes, which can be considered as minimal repair. A flow meter may experience several minimal repair events over its lifetime that are called recurrent events. However, if critical components (e.g., transmitters body) fail, the whole flow meter needs to be replaced according to its unique mechanical structures. Second, incomplete records of flow meters generally exist. If a flow meter has been installed before the company began careful archival record keeping, then the data for this flow meter will be left-truncated since the installation date is unavailable. Right-censored data are generated from the flow meters that they are still in service when the data are analyzed. Therefore, we need to develop an effective strategy for reliability analysis of flow meters to address multiple failure modes based on complicated field data.

In this paper, we use the nonhomogeneous Poisson process (NHPP) model with power-law intensity functions to analyze the failure mechanism of flow meters. This model is suitable to model recurrent events data with multiple failure modes and can also handle the standard right-censored cases [4]. Left-truncated data will be carefully considered by estimating the installation date according to the limited history information such as the manufacturing date [5]. Maximum likelihood

978-1-7281-3690-5/20/$31.00 ©2020 IEEE

method is used for model inference. Furthermore, random weighted likelihood bootstrap procedure [6] is used to address the statistical uncertainty of estimated parameters.

2 LITERATURE REVIEW

Reliability analysis has been extensively studied for many industry systems and various statistical models are developed. For non-repairable systems, lifetime models are commonly used such as the exponential, Weibull, normal, lognormal, and gamma distributions [7], which are appropriate for one failure mode data. For repairable systems, point process theory is the main tool for modeling failure data. For example, renewal process (RP) and nonhomogeneous Poisson process (NHPP) are the two most well-known models, which are strictly applicable only under perfect repair and minimal repair assumptions, respectively [4, 8, 9]. Specifically, RP is used to model a stochastic process in which the different times to failure of a system are considered independently and identically distributed random variables, which is consistent with the perfect repair assumption that the system will be as good as new after each repair. Applications of RP are limited due to the strong assumption of perfect repair. The NHPP, on the other hand, is used to model the failure process of a repairable system with minimal repairs, i.e., the system is repaired to be as bad as old for each failure. The assumption is appropriate for many repairable systems such as automobiles since typically only a small part (e.g., tire) of an automobile is repaired at a time. Thus, it is restored back to the condition close to the same as it was before the failure [10]. Both processes are special cases, to model the general behavior of the failure process (i.e., imperfect repair process), Brown and Proschan [11] propose an imperfect repair model, Kijima [12] introduces two types of virtual age models by reducing the system age after each repair, and Doyen and Gaudoin [13] develop two classes of imperfect repair models with nonhomogeneous Poisson process as a baseline while the repair effect is expressed by a reduction of failure intensity or a reduction of the system virtual age. Another class of general repair models is trend-renewal process (TRP) model, which includes both NHPP and RP models as special cases [8].

In many studies for reliability analysis, the event of primary interest is recurrent and thus could occur several times during the study period, for example, the breakdown of electro-mechanical systems (e.g., motor vehicles, subsystems in space stations, computers). Nelson [14] provides many examples and data analysis methods for recurrent event data. Cook and Lawless [15] present several examples from medical studies, which is another useful resource for models and methods. And a review paper by Peña [16] gives examples from both medical and reliability studies. In reliability applications, Xu et al. [17] extend the TRP model to describe replacement events in a multi-level repairable system (e.g., system, subsystem, and component levels) that may experience multiple replacement events at different levels over time. Hong et al. [18] use an NHPP model with a bathtub intensity function to describe window-observed recurrent failures of two failure modes for a service industry company, which requires a high level of system availability. To deal with multiple failure modes problem, an alternative approach is to use proportional hazards model, utilizing cause-specific hazard functions and time-dependent covariates for analysis of failure time with competing causes of failure [19].

In our paper, we use NHPP model to analyze the failure mechanism of flow meters given limited information about the failure process and complicated field data structure. NHPP is shown to have the ability to model recurrent event data with multiple failure modes and has simple inference procedures [18].

The remainder of this paper is organized as follows. Section 3 introduces the failure process of flow meters and describes the NHPP model including parameter estimation method. Numerical results for real-world flow meters failure data are provided in Section 4. Section 5 contains concluding remarks and areas for future research.

3 MODEL DEVELOPMENT

3.1 System Description

During the service life of a flow meter, an outage (failure) event is defined as a situation that makes it unavailable for functioning, e.g., the flow meter is not reading or reading wrong due to electronic failures, coil loosing, or transmitter failures. The recorded field data often have a complicated structure. Different electro-mechanical parts of a flow meter may fail during its lifetime, resulting in multiple failure modes and requiring different types of repair. For example, failed electronics need to be replaced, loosing coils need to be tightened, and blocked tubes need to be cleaned, which can be considered as three different failure modes. But all these repairs can be considered as minimal repair since the state of the flow meter is almost the same as it was before failure. Moreover, these failures may occur several times over the lifetime of a flow meter, called as recurrent events. However, other failure modes arising from critical parts such as transmitters require replacement of the entire flow meter due to its unique mechanical structures. Engineering knowledge suggests that it is reasonable to assume that these failure modes are independent. When a flow meter is replaced, it will be considered as a new unit and experience the same failure process after installed.

Information of failure times and maintenance records is available after the company began careful archival record keeping, which makes the flow meters installed before it be viewed as the left-truncated cases. An alternative way is to determine the most likely estimated date for installation date, either the manufacturing date [5] or the earliest recoded date that can be found before the archival recode system is built. In addition, it usually happens that flow meters are still in service at the “data-freeze” point, which are considered as the right-censored cases. The NHPP model used in this paper will be presented to be very suitable for recurrent failure data with multiple failure modes and be able to handle right-censored cases.

3.2 An NHPP Model

To model repairable system with minimal repairs, NHPP is commonly used in the literature, with the ability to handle multiple failure modes and recurrent events. An implicit assumption is that flow meters are repaired or replaced immediately after failure since we are interested in modeling and estimation of the probability mechanisms behind failure occurrences. The well-known power-law intensity function [18] is used in this paper to model the increasingly deteriorating process of flow meters, which is

$$\lambda(t;\beta,\eta)=\left(\frac{\beta}{\eta}\right)\left(\frac{t}{\eta}\right)^{\beta-1},\quad \beta>1, \tag{1}$$

where is η a scale parameter and β is a shape parameter. The corresponding cumulative intensity function is defined as

$$\Lambda(t;\beta,\eta)=\int_0^t \lambda(u;\beta,\eta)du=\left(\frac{t}{\eta}\right)^{\beta}, \tag{2}$$

giving the expected cumulative number of events from time 0 (i.e., the time or estimated time of installation) to time t.

The failure intensity function for each failure mode will be modeled separately. Let $\lambda_k(t;\beta_k,\eta_k)$ denote the intensity function for failure mode k (k = 1, 2, …, K, where K is the number of failure modes). Further, the overall intensity for the flow meters will be

$$\lambda(t;\Theta)=\sum_{k=1}^{K}\lambda_k(t;\beta_k,\eta_k), \tag{3}$$

where $\Theta=(\beta_1,\eta_1,\ldots,\beta_K,\eta_K)$. For the i^{th} (i = 1, 2, …, n) flow meter, the time scale is from time 0 to a specific ending timepoint T_i, which is either the replacement time of the flow meter or the "data-freeze" time since we consider the replaced flow meter as a new unit. The successive failure events are recorded by t_{ij} and each event is labeled with a failure mode Δ_{ij} taking values from {1, 2, …, K }, j =1, …, $N_i(T_i)$, where $N_i(T_i)$ counts the number of failure events irrespective of the failure modes for unit i during the observation window $(0, T_i)$. We then use the marked event process (t_{ij}, Δ_{ij}), j =1, …, $N_i(T_i)$, i = 1, 2, …, n, to represent the failure process.

3.3 Parameter Estimation

Maximum likelihood estimate (MLE) is used for the NHPP model inference. Given the time-to-event data with multiple failure modes, the likelihood function can be calculated by [20]

$$L(\Theta\mid \text{data})=\prod_{i=1}^{n}\left\{\prod_{j=1}^{N_i(T_i)}\lambda_{\Delta_{ij}}(t_{ij})\times\exp\left[-\int_0^{T_i}\lambda(u)du\right]\right\}. \tag{4}$$

Here, Θ is the parameter vector that denotes all parameters in the model and the MLE $\hat{\Theta}$ is obtained by maximizing the likelihood function in Equation (4). The likelihood function is valid under the assumption that T_i is a stopping time, which means its value depends stochastically only on the past history. Particularly, this property still holds for the right-censored cases, where T_i is independent of the failure process [4].

The estimations of parameters depend heavily on the collected data and will fluctuate among different sample data, especially when the sample size n is small. To account for the statistical uncertainty, bootstrap re-sampling methods are commonly used to provide approximate confidence intervals of estimated parameters. However, due to complicated data structure and sparsity of failures, traditional bootstrap re-sampling method will have poor performance in our case. Thus, the random weighted likelihood bootstrap procedure [6], which has been considered to be effective and easy-to-use for complicated problems, is used in our paper. The procedure proceeds as follows [5].

1) Simulate random values z_i, i = 1, 2, …, n, independently from the continuous distribution Gamma(1, 1).
2) The random weighted likelihood is

$$L^*(\Theta\mid \text{data})=\prod_{i=1}^{n}\left\{\prod_{j=1}^{N_i(T_i)}\lambda_{\Delta_{ij}}(t_{ij})\times\exp\left[-\int_0^{T_i}\lambda(u)du\right]\right\}^{z_i}. \tag{5}$$

3) Obtain the MLE $\hat{\Theta}^*$ by maximizing $L^*(\Theta\mid \text{data})$.
4) Repeat steps 1) − 3) M times to get M bootstrap samples $\hat{\Theta}^*_m$, m = 1, 2, …, M.

The distribution of $\sqrt{n}(\hat{\Theta}^*-\hat{\Theta})$ can be used to approximate the distribution of $\sqrt{n}(\hat{\Theta}-\Theta)$ if the weights z_i are generated from a continuous distribution with property $E(z_i) = [Var(z_i)]^{1/2}$ [21]. The results are insensitive to the choice of this continuous distribution and Gamma(1, 1) is used in our paper.

Based on MLE $\hat{\Theta}$, the reliability function can be obtained as

$$R(t;\hat{\Theta})=e^{-\int_0^t \lambda(u;\hat{\Theta})du}, \tag{6}$$

and the mean time to failure (MTTF) can be computed by

$$MTTF=\int_0^{\infty} R(t;\hat{\Theta})dt. \tag{7}$$

Furthermore, an approximate confidence interval of MTTF can be obtained from $\int_0^{\infty} R(t;\hat{\Theta}^*_m)dt$, given bootstrap samples $\hat{\Theta}^*_m$.

4 CASE STUDY

Real-world flow meter failure data from a process industry company are used in our case study. The recorded flow meter operating history has a complicated structure, so we need to preprocess the raw data first. Due to sparsity of failures, we consider two failure modes for flow meters in this paper. Failure mode 1 (FM1) contains all the small part failures with minimal repair no matter which part is failed, including replacing the failed electronics, tightening the loosing coils and cleaning the tubes. And failure mode 2 (FM2) is used to describe all the critical part failures such as transmitter, requiring replacement of the entire flow meter. After taking out the irrelevant information, all maintenance records will be labeled as FM1/FM2 according to the repair descriptions, which have been well kept in the archival record system since 1999. Data are organized according to the process locations. There are 21 different locations in the dataset and it will be considered as a new unit once replacement performed. In other words, each unit may experience several minimal repairs (FM1) or no repairs until its complete failure (FM2) or the "data-freeze" time. Flow meters that are still in service after February 28th, 2019 ("data-freeze" date) are considered as right-censored data and flow meters that were functioning before the record system is built are considered as the left-truncated data, in which case, the earliest recording date or the manufacturing date will be used as the estimated installation date for analysis purpose. For example, as illustrated in Figure 1, all records for process location F42XX (Full information is not shown here to protect sensitive and proprietary information) will be divided into three different units because two replacements occurred in this position. The first unit (red) was functioning before 1999, so the earliest recording date (January 1st, 1996) provided by the company is used to estimate the installation date. The second unit (blue) has exact installation date which is the replacement time of the first unit. The third unit (green) is right-censored since it is still in service after "data-freeze" date. Table 1 presents the data details, including the number of process locations from raw dataset, number of units after preprocessing, number of failures for each failure mode and numbers of left-truncated and right-censored cases.

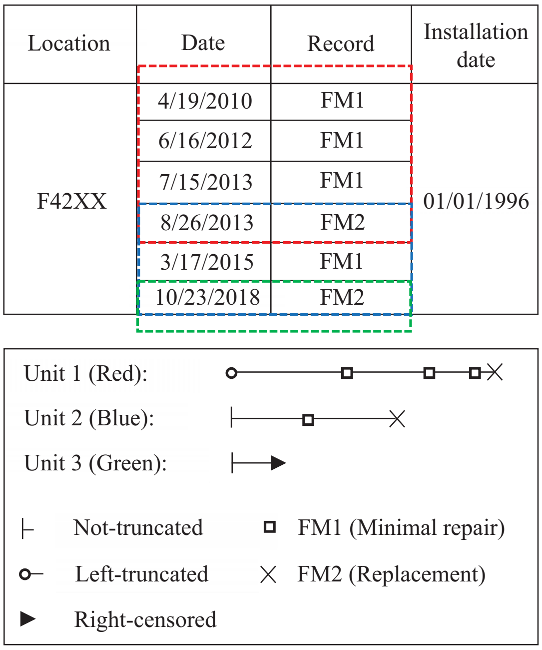

Figure 1 – Illustration for data preprocessing procedure

Table 1 – Summary of analyzed data

Process location	Unit	FM1	FM2	Left-truncated	Right-censored
21	47	35	28	13	18

As presented previously, two power-law intensity functions will be used to describe failure mode 1 (i.e., small part failure with minimal repair) and failure mode 2 (i.e., critical part failure with replacement), respectively. Preprocessed data are used to estimate the parameters $\Theta = (\beta_1, \eta_1, \beta_2, \eta_2)$. Based on the MLEs, the estimated intensity functions for failure mode 1 and failure mode 2 are expressed as

$$\hat{\lambda}_1(t) = \frac{1.313t^{0.313}}{30.512}, \quad (8)$$

$$\hat{\lambda}_2(t) = \frac{1.613t^{0.613}}{89.204}, \quad (9)$$

respectively. The estimated overall intensity function is

$$\hat{\lambda}(t) = \hat{\lambda}_1(t) + \hat{\lambda}_2(t), \quad (10)$$

which are presented in Figure 2. It shows that failures for FM1 are more frequent than FM2 in the early age of a flow meter, indicating small parts failures are more likely to occur in the first 15 years. Table 2 shows the MLEs and 95% approximate confidence intervals (CIs) for the parameters of both failure modes using random weighted likelihood bootstrap method.

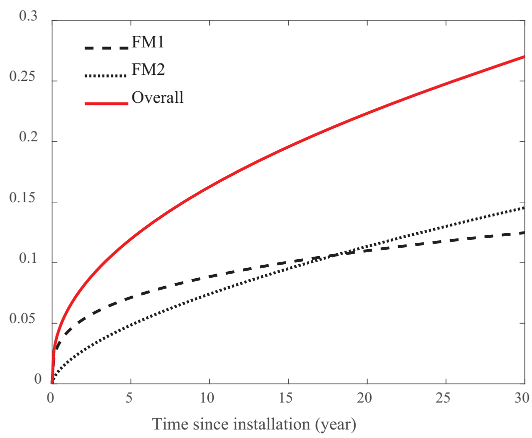

Figure 2 – Estimated intensity functions

Table 2 – MLEs and 95% CIs for parameters of both failure modes

Failure mode	Parameter	MLE	Std. err.	95% CI Lower	95% CI Upper
FM1	β_1	1.313	0.323	1.049	2.165
	η_1	13.508	2.279	10.563	19.322
FM2	β_2	1.613	0.331	1.207	2.483
	η_2	16.187	1.583	13.169	19.242

The corresponding cumulative functions, shown in Figure 3, can provide the expected cumulative number of failures given specific time interval. The estimated cumulative intensity function for the first failure mode is given by

$$\Lambda_1\left(t;\hat{\beta}_1,\hat{\eta}_1\right) = \left(\frac{t}{13.508}\right)^{1.313}, \quad (11)$$

and for the second failure mode, it is presented as

$$\Lambda_2\left(t;\hat{\beta}_2,\hat{\eta}_2\right) = \left(\frac{t}{16.187}\right)^{1.613}. \quad (12)$$

To assess goodness of fit, we compare the observed number of failures with the estimated expected cumulative number of failures. The observed overall number of failures is the total number of failures for both failure modes that occurred by time t. There are 47 units in the dataset, having different observation windows. Therefore, the expected overall cumulative number of failures for all units from time 0 to time t is adjusted by

$$E(t;\hat{\Theta}) = \sum_{i=1}^{n}\sum_{k=1}^{2} \Lambda_k \left(\min\{t, T_i\}; \hat{\beta}_k, \hat{\eta}_k \right), \tag{13}$$

where T_i is the endpoint of the observation window for unit i.

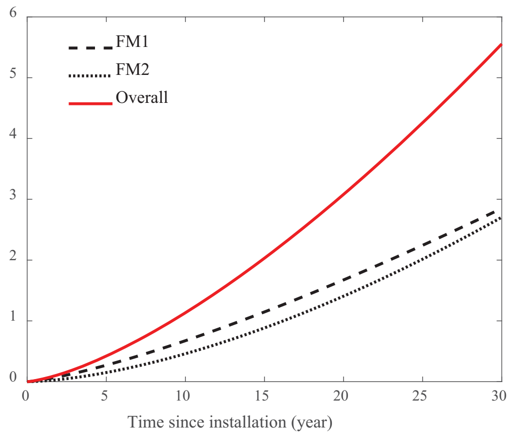

Figure 3 – Estimated cumulative intensity functions

Figure 4 presents the observed overall cumulative number of failures (black dots) and the estimated expected overall cumulative number of failures (red solid line) with approximate 95% pointwise CIs (red dashed line), which are derived from the bootstrap samples. The actual cumulative numbers of failures are almost within the estimated CIs, which shows that the parametric model for the overall failures can reasonably fit the observed failure data.

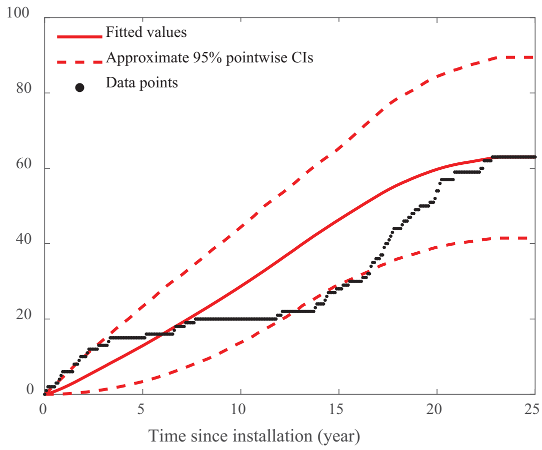

Figure 4 – Observed overall cumulative number of failures (black dots) and estimated expected overall cumulative number of failures (red solid line) with approximate 95% pointwise CIs (red dashed line)

In addition, based on MLE $\hat{\Theta}$, the CDF of flow meter lifetime can be derived as

$$F(t;\hat{\Theta}) = 1 - R(t;\hat{\Theta}), \tag{14}$$

presented in the Figure 5. The corresponding MTTF is computed to be around 8.3 years with approximate 95% confidence interval [6.57, 10.82]. The estimated MTTF is very useful for the company to design better inspection and maintenance scheduling.

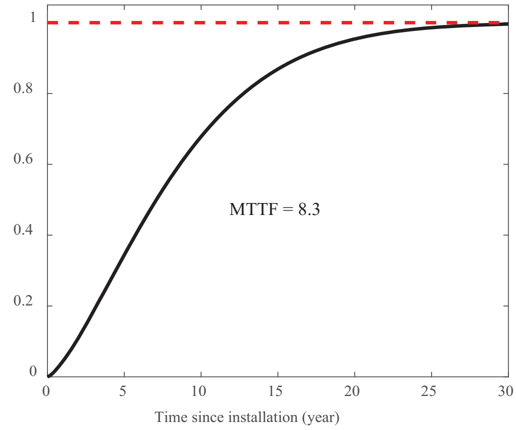

Figure 5 – CDF of flow meter lifetime

5 CONCLUSION

In this paper, we conduct reliability analysis of flow meters based on complicated field data using the NHPP model with power-law intensity functions to address multiple failure modes. The proposed framework is flexible and can handle left-truncated and right-censored cases well. Numerical results provide estimated intensity functions for important failure modes to help a process industry company have in-depth understanding of the flow meters failure mechanism. Besides, the model can quantify the mean time to failure of a flow meter, providing useful information to design inspection and maintenance schedules and spares inventory policy. Although the discuss of this paper is heavily on the basis of flow meters failure data, for other systems sharing similar data structure, the presented analysis method can also be applied to achieve the same goals.

In this paper, we do not consider the changes in operational conditions, which affects the failure mechanisms of devices such as flow meters. A natural extension is to incorporate the effects of operational conditions into the reliability model. These factors that may be constant over time (e.g., design, material) or variable over time (e.g., temperature) are modeled as covariates by means of a proportional intensity process to modify the baseline intensity functions. It is also critical to develop effective maintenance and spare parts inventory policies based on reliability models to achieve better system performance.

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