Age-based Maintenance Scheduling For Flowmeters With Multiple Failure Modes And Covariates

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SUMMARY

Reliability assessment and maintenance scheduling of flowmeters are of great importance for process industry companies because of the need to ensure the production quality and reduce operational risks and costs. In practice, the failure process of flowmeters is complicated due to multiple failure modes arising from different electro-mechanical parts. Besides, there generally exists heterogeneity among the flowmeters that is caused by several factors (i.e., covariates) such as operational conditions. In this paper, we use the nonhomogeneous Poisson process (NHPP) model with covariates to assess the reliability of flowmeters and then derive the optimal age-based preventive maintenance (PM) policy based on the estimated reliability model. The effects of covariates are incorporated in the reliability model by means of a proportional intensity function. We apply the maximum likelihood method to estimate the model parameters and adopt the random weighted likelihood bootstrap procedure to address the statistical uncertainty. Real-world flowmeters failure data from a process industry company are used in the case study. The estimated intensity functions are shown to reasonably fit the failure data and the obtained optimal PM policies provide cost-efficient and covariate-specific maintenance strategy for the company.

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]. However, Coriolis meters are typically expensive because of high manufacturing quality requirements and the relatively larger size [2]. Unexpected failures of flowmeters will cause a shutdown of the production process, resulting in a large amount of downtime cost, and may also cause safety problems for the operational environments. Therefore, reliability assessment and maintenance scheduling of flowmeters is of great importance for process industry companies.

In practice, reliability assessment and maintenance scheduling of flowmeters is challenging for the following reasons. First, during the service life of a flowmeter, 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 flowmeter 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 repairs. A flowmeter may experience several minimal repairs over its lifetime that are called recurrent events. However, if critical components (e.g., transmitters body) fail, the whole flowmeter needs to be replaced according to its unique mechanical structures. Second, in actual maintenance practice, the failure process of flowmeters may be dependent on many factors (i.e., covariates) such as operational conditions (e.g., temperature, process type, tube material). For example, flowmeters which are used to measure acidic and caustic fluids are more likely to fail than the one with water going through it. Moreover, incomplete records of flowmeters generally exist. If a flowmeter has been installed before the company began careful archival record keeping, then the data for this flowmeter will be left-truncated since the installation date is unavailable. Right-censored data are generated from the flowmeters that are still in service when the data are analyzed. Therefore, we need to develop an effective framework for reliability assessment and maintenance scheduling of flowmeters to address multiple failure modes and covariates based on complicated field data.

In this paper, we use the nonhomogeneous Poisson process (NHPP) model with proportional intensity functions [3] to analyze the failure process of flowmeters. The estimated reliability model is then used to derive the covariate-specific PM policy. The NHPP 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. Maximum likelihood method is used for model inference. Furthermore, random weighted likelihood bootstrap procedure [5] is used to address the statistical uncertainty of estimated parameters.

2 LITERATURE REVIEW

The reliability of repairable systems has been commonly studied by using point process models. The renewal process (RP) and the nonhomogeneous Poisson process (NHPP) are the two commonly used models for repairable systems, which are strictly applicable only under perfect repair and minimal repair assumptions, respectively [6, 7]. Specifically, RP is used to model the failure process of a system that 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. Both processes are special cases, to model the general behavior of the failure process (i.e., imperfect repair process), Lindqvist et al. [6] propose a trend-renewal process (TRP) model, which includes both NHPP and RP models as special cases.

In reliability analysis of electro-mechanical systems (e.g., motor vehicles, flowmeters), the event of primary interest can arise from different parts of the system and may occur several times during the study period. Hong et al. [8] 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. Liao et al. [9] conduct reliability analysis of flowmeters based on complicated field data using the NHPP model to address multiple failure modes. To incorporate the effects of covariates, the proportional hazards model (i.e., Cox regression model) is commonly used [3], which is composed of two parts, i.e., the baseline intensity function and a link function with covariates that has either an exponential, log, or logistic form. The Cox regression model can be taken into consideration for the reliability analysis which considers either perfect, minimal, or imperfect repairs [7].

The maintenance planning of productive systems is vital to improve system availability and reduce operational risks and costs. Typically, age-based PM optimization is to obtain the optimal PM cycle that minimizes the long-run operating cost rate or maximizes the system availability. In our paper, we use the NHPP model with proportional intensity functions to analyze the failure mechanism of flowmeters with multiple failure modes and covariates. We aim at providing cost-efficient and covariate-specific PM policy for flowmeters based on the estimated reliability model.

The remainder of this paper is organized as follows. Section 3 introduces the failure process of flowmeters and describes the NHPP model with covariates including parameter estimation method. Section 4 presents age-based preventive maintenance modeling of flowmeters. Numerical results for real-world flowmeters failure data are provided in Section 5. Section 6 contains concluding remarks and areas for future research.

3 RELIABILITY ASSESSMENT

3.1 *System Description*

During the service life of a flowmeter, an outage (failure) event is defined as a situation that makes it unavailable for functioning, e.g., the flowmeter 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 flowmeter may fail during its lifetime, resulting in multiple failure modes and requiring different types of repair. For example, failed electronics need to be replaced, and loosing coils need to be tightened, which can be considered as two different failure modes. But all these repairs can be considered as minimal repairs since the condition of the flowmeter is almost the same as it was before failure. These failures may occur several times over the lifetime of a flowmeter, called as recurrent events. However, other failure modes arising from critical parts such as transmitters require replacement of the entire flowmeter due to its unique mechanical structures. When a flowmeter is replaced, it will be considered as a new unit and experience the same failure process after installed. Engineering knowledge suggests that it is reasonable to assume that all these failure modes are independent. Moreover, the failure process of flowmeters can be affected by operational conditions, which may be constant over time (e.g., process type) or variable over time (e.g., temperature). These factors provide additional information about the failure mechanisms of flowmeters, which need to be incorporated as covariates in the reliability model.

Information of failure times and maintenance records is available after the company began careful archival record keeping, which makes the flowmeters installed before it be viewed as the left-truncated cases. An alternative way is to determine the most likely estimated date for installation date, such as the earliest recoded date that can be found before the archival recode system is built. In addition, it usually happens that flowmeters are still in service at the "data-freeze" point, which are considered as the right-censored cases. The NHPP model with covariates 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 *NHPP Model with Covariates*

In our previous work [9], the NHPP with power-law intensity functions is used to model the failure process of flowmeters. However, there generally exist various covariates (e.g., process type) that affect the failure mechanisms of flowmeters and have not been considered. In this paper, we extend our previous work by incorporating the effects of covariates in the reliability model by means of a proportional intensity function [3] to modify the baseline intensity. The proportional intensity function is given as

$$\lambda(t;\beta,\eta,\boldsymbol{\alpha}) = \left(\frac{\beta}{\eta}\right)\left(\frac{t}{\eta}\right)^{\beta-1} \exp\left(\boldsymbol{\alpha x}\right), \tag{1}$$

where $\boldsymbol{x}$ is the vector of covariates and the corresponding coefficients are denoted by $\boldsymbol{\alpha}$. Note that $\boldsymbol{x}$ can be a function of time for time-varying covariates. The cumulative intensity function is computed as

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

giving the expected cumulative number of failures 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 $\lambda_k(t;\beta_k,\eta_k,\boldsymbol{\alpha}_k)$ denote the intensity function for failure mode k (k = 1, 2, …, K, where K is the number of failure modes). Specifically, we use the first (K−1) failure modes to describe different types of small part failures (e.g., electronics, coils, and tubes) and the failure mode K contains all critical part failures (e.g., transmitters). Further, the overall intensity for the flowmeters will be

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

where $\Theta = (\beta_1, \eta_1, \boldsymbol{\alpha}_1, \ldots, \beta_K, \eta_K, \boldsymbol{\alpha}_K)$. For the i^{th} (i = 1, 2, … , n) flowmeter, the time scale is from time 0 to a specific ending timepoint T_i, which is either the replacement time of the flowmeter or the "data-freeze" time since we consider the replaced flowmeter 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 model inference. Given the time-to-event data with multiple failure modes, the likelihood function can be computed by [10]

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

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. The random weighted likelihood bootstrap procedure [5], which has been considered to be effective and easy-to-use for complicated problems, is used in our paper. The procedure proceeds as follows.

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

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

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 $E(z_i) = [\mathrm{Var}(z_i)]^{1/2}$ [11]. 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

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

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 *AGE-BASED MAINTENANCE POLICY*

In our motivated application, flowmeters have multiple failure modes arising from different electro-mechanical parts, which require different types of maintenance. It is desirable to develop cost-effective maintenance strategy for flowmeters in the process industry. In this paper, we consider age-based maintenance policy for flowmeters based on the estimated reliability model. To address multiple failure modes, three different types of maintenance are defined as follows.

- Preventive maintenance (PM). PM is a periodic practice and is scheduled after every τ units of time. It is performed with a fixed cost c_{PM}, which instantly returns the flowmeter to a like-new condition.
- Corrective maintenance (CM). When a critical part fails (i.e., failure mode K), the flowmeter needs to be replaced with a fixed cost c_{CM} and we have $c_{CM} > c_{PM}$. After CM, the flowmeter returns to be as-good-as-new.
- Minimal repair (MR). Between two successive replacements (PM/CM), i.e., in a renewal cycle, several minimal repairs are performed when small parts fail (i.e., failure mode 1, … , K−1). The MRs caused by failure mode k have a fixed cost $c_{MR,k}$, k =1, … , K−1. All MRs only restore the function of the flowmeter to the condition just before the failures.

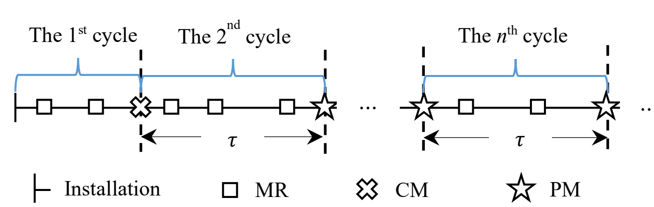


Figure 1 – Illustration of the renewal-award process of flowmeters

All types of maintenance are assumed to be performed

instantaneously since the maintenance times are negligible in one renewal cycle. Figure 1 illustrates the described renewal-award process of flowmeters. From Figure 1, we can see that each renewal cycle ends with either a PM or a CM.
The expected cycle length, denoted by μ, is derived as

$$\begin{aligned}\mu &= \int_0^{\tau} t f_K(t)\,dt + \tau R_K(\tau) = \int_0^{\tau} R_K(t)\,dt \\ &= \int_0^{\tau} e^{-\int_0^t \lambda_K(u;\beta_K,\eta_K,\alpha_K)\,du}\,dt = \int_0^{\tau} e^{-\Lambda_K(t;\beta_K,\eta_K,\alpha_K)}\,dt.\end{aligned} \tag{8}$$

The expected cost for each renewal cycle is given by

$$\begin{aligned}C &= R_K(\tau)\left(c_{PM} + \sum_{k=1}^{K-1} c_{MR,k}\Lambda_k(\tau)\right) \\ &\quad + \left(1-R_K(\tau)\right)\left(c_{CM} + \sum_{k=1}^{K-1} c_{MR,k}\Lambda_k\left(\mu - \tau R_K(\tau)\right)\right).\end{aligned} \tag{9}$$

Finally, the long-run expected cost rate is given by

$$\eta = \frac{C}{\mu}. \tag{10}$$

The optimal age-based PM policy τ^* is then obtained by minimizing η.

5 CASE STUDY

Real-world flowmeter failure data from a process industry company are used in our case study. The recorded flowmeter 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 (i.e., K=2) for flowmeters 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. Failure mode 2 (FM2) is used to describe all the critical part failures such as transmitter, requiring replacement of the entire flowmeter. 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 75 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. Flowmeters that are still in service after January 31st, 2020 ("data-freeze" date) are considered as right-censored data and flowmeters 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 2, 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.

Location	Date	Record	Installation date
F42XX	4/19/2010	FM1	01/01/1996
	6/16/2012	FM1	
	7/15/2013	FM1	
	8/26/2013	FM2	
	3/17/2015	FM1	
	10/23/2018	FM2	

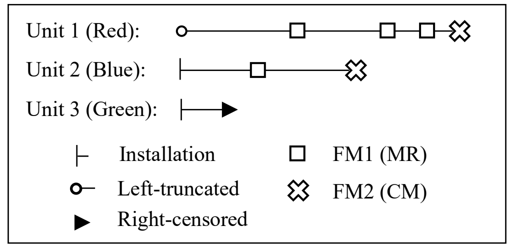


Figure 2 – Illustration for data preprocessing procedure

Moreover, these flowmeters are functioning under different operational conditions such as temperature and process type. Based on the expert experiences, the process type has significant impacts on the failure process of flowmeters, which is considered as the covariate in this case study. There exist various process types such as water, nitrogen, and sulfuric acid. Instead of examining the impact of each specific process type, we categorize these process types into two levels: critical level (e.g., sulfuric acid) and non-critical level (e.g., water) according to the engineering knowledge. We use x to denote the process type level and x takes values 1 and 0, which is an indicator variable for the critical level.

Two separate proportional intensity functions are used to describe FM1 and FM2, which are given as

$$\lambda_k(t;\beta_k,\eta_k,\alpha_k) = \left(\frac{\beta_k}{\eta_k}\right)\left(\frac{t}{\beta_k}\right)^{\beta_k-1}\exp\left(\alpha_k x\right), \quad k=1,2, \tag{11}$$

where x=0,1. We use the preprocessed data to estimate the parameters Θ = (β_1, η_1, α_1, β_2, η_2, α_2) and Table 1 shows the MLEs and respective standard errors of parameters for both failure modes using random weighted likelihood bootstrap method.

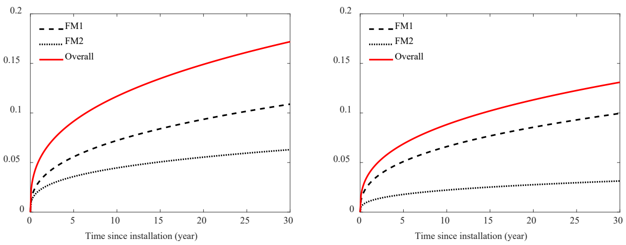
Table 1 – MLEs and standard errors of parameters for both failure modes

Failure mode	Parameter	MLE	Std. err.
FM1	β_1	1.37	0.17
	η_1	17.04	1.99
	α_1	0.09	0.22
FM2	β_2	1.31	0.17
	η_2	38.67	5.38
	α_2	0.70	0.23

Based on the MLEs, the estimated intensity functions for two failure modes are given as

$$\lambda_1(t) = \frac{1.37t^{0.37}}{48.65}\exp(0.09x), \quad \lambda_2(t) = \frac{1.31t^{0.31}}{120.08}\exp(0.7x). \quad (12)$$

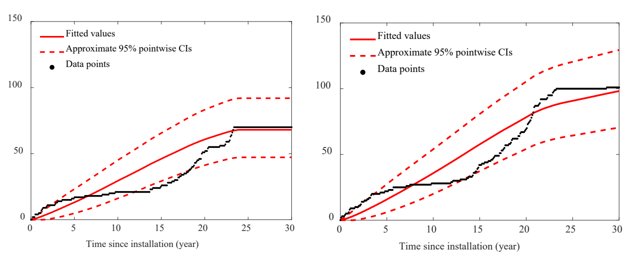
Let x take value 1 and 0 in Equation (12), and we can obtain the estimated intensity functions for both failure modes under the critical process type level and non-critical level, respectively.



(a) Critical level (b) Non-critical level

Figure 3 – Estimated intensity functions for both levels

Figure 3 shows these estimated intensity functions. We can see that in both cases, the failures for FM1 are more frequent than FM2 during the lifetime of flowmeters, indicating that small parts failures are more likely to occur than critical parts failures. In addition, the effects of the covariate x on the failure process are reflected in the exponential terms of Equation (12). Both MLEs of α_1 and α_2 are positive, which means that flowmeters with process type in the critical level have more frequent failures for both failure modes. This effect leads to smaller MTTF of flowmeters with critical process type. Therefore, for the critical level, more frequent PM needs to be scheduled to ensure the functioning of the flowmeters and reduce downtime costs caused by unexpected failures.



(a) Critical level (b) Non-critical level

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)

To assess goodness-of-fit of the proposed model, we compare the observed overall number of failures with the estimated expected cumulative number of failures for both process type levels. The observed overall number of failures is the total number of failures for both failure modes that occurred by time t. There are 53 and 78 units for the critical and non-critical levels respectively, having different observation windows. Therefore, the expected overall cumulative number of failures for all units in each process type level from time 0 to time t is adjusted by

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

where T_i is the endpoint of the observation window for unit i. 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. For both levels, 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.

Based on the estimated intensity functions, we compute the MTTF and respective confidence interval (CI). Table 2 presents the estimated MTTF and the 95% CI for both levels. We can see that the MTTF of flowmeters with process type in the critical level is approximate 2.4 years smaller than the non-critical level. It is verified that the covariate (i.e., process type) has significant effects on the failure process of flowmeters.

Table 2 – MTTF and 95% CI for both process type levels (years)

Process type level	MTTF	95% CI	
		Lower	Upper
Critical (x=1)	10.10	8.08	12.12
Non-critical (x=0)	12.51	9.82	15.21

We further derive the age-based PM policy. For illustrative purpose, the maintenance costs are specified as

$$c_{PM} = 300, \quad c_{CM} = 2000, \quad c_{MR} = 50. \quad (14)$$

As discussed in Section 4, the optimal age-based PM policy τ^* is obtained by minimizing the long-run expected cost rate η. We summarize the PM policies for both levels in Table 3.

Table 3 – Optimal age-based PM policies for both process type levels (years)

Process type level	τ^*	η^*
Critical (x=1)	15.82	90.59
Non-critical (x=0)	26.35	54.60

For the process types in the critical level, the optimal PM cycle is 15.82 years, which obtains the minimum long-run expected cost rate 90.59. It means that the flowmeter is replaced when its age reaches 15.82 years old or its critical parts fail, whichever comes first. For the non-critical level, the optimal PM cycle is 26.35 years. We can see that the PM is scheduled less frequent than the critical level. This result provides process type level-specific and cost-efficient maintenance policies for the company to achieve better system performance.

6 CONCLUSION

In this paper, an efficient framework is developed for reliability assessment and maintenance scheduling of flowmeters. We use the NHPP model with covariates to analyze the reliability of flowmeters with multiple failure modes and complicated field data. Based on the estimated reliability model, we obtain covariate-specific and cost-efficient PM policy. The proposed framework is flexible and can handle left-truncated and right-censored cases well. Numerical results present the additional effects caused by covariates in the estimated intensity functions for important failure modes. Besides, the estimated mean time to failure and derived PM policy under different process type levels provides implementation recommendation for the company to design inspection and maintenance schedules. Although the discuss of this paper is heavily on the basis of flowmeters failure data, for other systems sharing similar data structure, the developed framework can also be applied to achieve the same goals.

In this analysis, we address the heterogeneity by using a covariate (i.e., process type). However, in practice, two flowmeters that have the same process type may experience different failure processes. An extension is to address this unit-to-unit variability by introducing random effects.

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