Reliability Engineering and System Safety 106 (2012) 160–164

Contents lists available at SciVerse ScienceDirect

Reliability Engineering and System Safety

journal homepage: www.elsevier.com/locate/ress

Forecasting warranty claims for recently launched products

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ARTICLE INFO

Article history:
Received 29 August 2011
Received in revised form
20 May 2012
Accepted 6 June 2012
Available online 15 June 2012

Keywords:
Non-homogenous Poisson process (NHPP)
Warranty claims
Forecasting
Constrained maximum likelihood estimation

ABSTRACT

Forecasting warranty claims for recently launched products that have short histories of claim records is vitally important for manufacturers in preparing their fiscal plans. Since the amount of historical claim data for such products is not large enough, developing forecasting models with good performance has been a difficult problem.

The objective of this paper is to develop an algorithm for forecasting the number of warranty claims of recently launched products. A two-phase modelling algorithm is developed: in Phase I, we estimate the upper and the lower bounds of the warranty claim rates of the reference products that have been in the market for a longer time; in Phase II, we build forecasting models for the recently launched products and assume that their future claim rates are subject to the bound constraints derived from Phase I. Based on this algorithm, we use the NHPP (non-homogeneous Poisson process) and the constrained maximum likelihood estimation to build forecasting models on artificially generated data as well as warranty claim data collected from an electronics manufacturer. The results show that the proposed algorithm outperforms commonly used NHPP models.

1. Introduction

In warranty management, forecasting the number of warranty claims is vitally important for manufacturers in preparing their fiscal plans. Starting with Kalbfleisch et al. [1], considerable research on forecasting warranty claims has been conducted (see [1,20,2–12,21], for example). A recently published review paper on warranty data analysis can be found in [13], which includes comments on different types of warranty forecasting techniques. In existing literature, however, there has been found little research on warranty claim forecasting for products that have short histories of claims (for example, those products that have only 3-month or 6-month claim data), although it is extremely important for the manufacturers to make better prediction of the number of warranty claims for their recently launched products.

The objective of this paper is to develop an algorithm for forecasting the number of warranty claims of a recently launched product, referred as *target product* in the following. We assume that the manufacturer has already received quite long records of warranty claim data of similar products that the manufacturer has produced and refer such products as *reference products*. A two-phase forecasting algorithm is proposed: in Phase I, we estimate the lower and the upper bounds of warranty claim rates of the reference products; in Phase II, we build forecasting models for the recently launched products and assume that the claim rates of the products lie in the bound constraints derived from Phase I.

Although this work is motivated by the desire to forecast warranty claims, the approach can also be used in similar cases such as inventory planning and insurance claim forecasting, when the historical data of reference products are available.

The remainder of this paper is structured as follows. Section 2 details the problems in warranty claim forecasting. Section 3 proposes an algorithm for forecasting warranty claims of recently launched products. Section 4 applies the proposed algorithm to both artificially generated data and warranty claim data collected from an electronics manufacturer, and compares the performance of the proposed algorithm to the commonly used algorithm. Discussion is carried out in Section 5. The final section concludes the paper.

2. Problem description

We assume that the claim data discussed in this paper are aggregated on a monthly basis. These data can be expressed as shown in Table 1. At a given calendar month T, our objective is to predict the total number of warranty claims that might be reported in the next K months. In Table 1, the number of warranty claims of a type of product shipped to the end-users in months i and then claimed in month j is denoted as $d_{i,j}$, and the predicted

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http://dx.doi.org/10.1016/j.ress.2012.06.008

Table 1
Field warranty data.

MoS	Shipments	Calendar months when claims are received.								
		1	2	3	…	T	$T+1$	$T+2$	…	$T+K$
1	S_1	$d_{1,1}$	$d_{1,2}$	$d_{1,3}$	…	$d_{1,T}$	$\hat{d}_{1,T+1}$	$\hat{d}_{1,T+2}$	…	$\hat{d}_{1,T+K}$
2	S_2		$d_{2,2}$	$d_{2,3}$	…	$d_{2,T}$	$\hat{d}_{2,T+1}$	$\hat{d}_{2,T+2}$	…	$\hat{d}_{2,T+K}$
3	S_3			$d_{3,3}$	…	$d_{3,T}$	$\hat{d}_{3,T+1}$	$\hat{d}_{3,T+2}$	…	$\hat{d}_{3,T+K}$
⋮	⋮				…		⋮			
T	S_k					$d_{T,T}$	$\hat{d}_{T,T+1}$	$\hat{d}_{T,T+2}$	…	$\hat{d}_{T,T+K}$

number of warranty claims is denoted as $\hat{d}_{i,j}$. 'MoS' stands for the month when the products are shipped to the end-users.

When T is large, one can develop a forecasting model with good performance as there is a long history of warranty claim data available. Research on such a forecasting problem can be found in [1–5,7,9–11,14,15]. Most of those publications, however, conduct little discussion on the availability of historical claim data. For a manufacturer, one of their important concerns is how to forecast the number of warranty claims when T is small. For example, $T=3$ or $T=6$, which means the manufacturer has only received warranty claims of the first 3 months or the first 6 months. This usually happens for those recently launched products.

3. Algorithm development

3.1. The algorithm

Modern manufacturing is characterised by often nearly identical products due to common components and technology being used [16]. This property has been used in warranty data analysis such as early detection of reliability problems (see [17], for example). Denote $\hat{r}_k$ as the estimated warranty claim rate of the target product during its k-th month. For early detection of reliability problems, the reference value for $\hat{r}_k$ is denoted by $\hat{r}_k^U$, which can be obtained from previous experience with similar products or design specifications, as assumed in [17]. Then the early detection of reliability problems can be formulated as a test of the multiple-parameter hypothesis [17]:

$$\hat{r}_1 \le \hat{r}_1^U, \hat{r}_2 \le \hat{r}_2^U, \ldots, \hat{r}_{T+K} \le \hat{r}_{T+K}^U \tag{1}$$

The above inequalities have also been used as an assumption in designing early detection algorithm (also see [18,19]). Similarly, we can assume that the other reference values for $\hat{r}_k$, denoted by $\hat{r}_k^L$, which can also be obtained from other reference products and satisfies

$$\hat{r}_1^L \le \hat{r}_1, \hat{r}_2^L \le \hat{r}_2, \ldots, \hat{r}_{T+K}^L \le \hat{r}_{T+K} \tag{2}$$

Denote the estimated claim rate of the i-th reference product in month k as $\hat{r}_{i,k}$. The inequalities in (1) and (2) can be used to build models for forecasting warranty claims, based on which we can derive a new algorithm to build a model for forecasting warranty claims as following:

- Assume that the claim rates of both the reference and the target products are stable over months in service[1].
- If the observed claim rates of the target product in the first T months are larger than the claim rates $\hat{r}_k^L$ derived from a set of reference products and less than the claim rates $\hat{r}_k^U$ derived from this set reference products for $k=1,2,\ldots,T$, then we can assume that the claim rates of the model in months $\{T+1,T+2,\ldots,T+K\}$ lie in $(\hat{r}_k^L,\hat{r}_k^U)$ for $k=T+1,T+2,\ldots,T+K$.

The above algorithm can also be re-written in Table 2.

3.2. Implementation of the algorithm

The non-homogeneous Poisson process (NHPP) is a stochastic process that has been widely used in the reliability engineering as well as in estimating warranty claims (see [9,10] for example).

Denote the total number of warranty claims of the target product in month k as d_k and the total number of the target product on the market as N. Then the likelihood function of the NHPP is given by

$$L_{NHPP} = \prod_{k=1}^{T} \frac{\left(N\int_{k-1}^{k} r(x)\,dx\right)^{d_k} e^{-(N\int_{k-1}^{k} r(x)\,dx)}}{d_k!} \tag{3}$$

where $r(x)$ is the intensity function of the NHPP, and $E(d_k) = N\int_{t-1}^{t} r(x)\,dx$. Thus the optimisation problem, based on the algorithm in Table 2, can be stated as

$$\text{Maximise} \quad L_{NHPP}$$
$$\text{Subject to} \quad \hat{r}_k^L \le \int_{k-1}^{k} r(x)\,dx \le \hat{r}_k^U \quad \text{for } k=T+1,T+2,\ldots,T+K. \tag{4}$$

The above algorithm is constrained maximum likelihood estimation (CMLE).

3.3. Discussion

The selection of reference products in Phase I in the algorithm proposed (in Table 2) is very important. For selecting such reference products, expert opinions or mathematical algorithms might be pursued. Mathematical algorithms such as the k-nearest-neighbour (K-NN) algorithm can be applied.

In this paper, we adopt the algorithm shown in Table 3.

One of the well-known phenomena of warranty data is *warranty data maturation*. This phenomenon witnesses that there is a tendency for the observed warranty claim frequencies to increase with time [20]. Different approaches have been suggested to tackle warranty data maturation in warranty data analysis. For example, Singpurwalla and Wilson suggested that a better approach would be the consideration of dynamic linear models, with innovation terms that account for the added uncertainties due to a maturation of the data [2]. Weighted regression modelling and weighted maximum likelihood estimation have also been suggested in [11,21]. In the present article, as the proposed algorithm (shown in 2) aims to find a region defined by the lower and upper bounds, which are not fixed values, the phenomena of warranty data maturation do not affect the efficiency of the algorithm significantly. This can be seen from the following data experiments, based on both artificially generated data and data collected from a manufacturer.

4. Data experiments

In this section, we evaluate the proposed algorithm shown in Table 3, based on artificially generated data and data collected from an electronics manufacturer, respectively.

We set $T=6$, 9, and 12, respectively, as the number of months that the recently launched products have been in the market and

[1] In practice, due to various reasons such as design modification, the claim rates of a product over month in service can change dramatically.