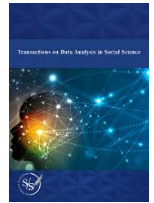




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# Modeling Mechanical Component Failures during the Two-Dimensional Base Warranty Period for a Locally Produced Car in Iran

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ARTICLE INFO	ABSTRACT
<p>Article History:            Received 2 June 2020            Received in revised form 11 September 2020            Accepted 11 December 2020            Available online 15 December 2020</p> <p>Keywords:            Two-Dimensional Base Warranty,            Product Failure Estimation,            Mechanical Components, Locally Produced Car</p>	<p>The sale of a product does not mark the end of the manufacturer's involvement, and providing services such as free repair of authorized product failures during the base warranty period is among the responsibilities and commitments of the manufacturer towards the customer. Fulfilling such commitments requires time and resources to identify and rectify failures. In such conditions, estimating the product failure process and associated costs can assist the manufacturer in providing the necessary provisions and resources for servicing and rectifying product failures during the base warranty period. In this article, data on failures of mechanical components of a locally produced car in Iran are collected during the two-dimensional base warranty period, and the probability distribution governing these failures is extracted. Subsequently, based on the mathematical model governing these failures, the expected number of failures is identified, and considering the cost of failures, the expected cost of repairing mechanical component failures is estimated. Finally, by interpreting these results, recommendations are provided for better estimating the failure process and associated costs.</p>

## 1. INTRODUCTION

Today, the responsibilities of manufacturers towards their products extend beyond production and presentation to the market. Prior to production and introduction, planning and provisions must be made to support the product during the warranty period. This enables the provision of satisfactory services, instills confidence in customers regarding the product's performance, and helps maintain and expand the product market. Accordingly, proper planning for warranty policies and estimating and ensuring the associated service costs can assist in preserving the manufacturer's position in today's competitive market. Among various products, automobiles play a key role in modern life. The warranty market for these products is vast and competitive, presenting manufacturers with numerous challenges in addressing customer demands for services, validating requests, identifying faults, estimating fault processes, predicting and ensuring service costs, supplying spare parts, utilizing fault data for improving production quality, and evaluating supplier performance. For example, global estimates indicate that approximately 2.6% of the total income of automobile manufacturers is allocated to covering basic warranty costs. On average,

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\$577 is spent for each produced car to cover basic warranty expenses [1]. Given the lower quality standard of our country's automobile and spare parts production, it can be expected that the costs associated with basic warranty periods are significantly higher than the global average. In such circumstances, product failure data during the basic warranty period can serve as valuable starting points for extracting and analyzing the product failure process, subsequently facilitating the prediction and estimation of costs related to basic warranty services.

A review of the literature on basic warranties indicates that the majority of research in the warranty domain has focused on mathematical modeling and academic analysis based on classical assumptions. For further familiarity with warranty and research conducted in this field, refer to [2-4]. In contrast, research addressing the study, examination, and analysis of real data and field product failures has been limited. This study aims to review research conducted in the field of products with basic warranties, such as automobiles, to understand the significance and role of real-world failure data in extracting and modeling the product failure process.

As one of the pioneering studies, Lawless and colleagues [5] proposed a model based on the cumulative operating time of automobiles to estimate the time to product failure. To achieve this, they initially estimated the customer's usage rate of the product and then extracted the time to product failure based on different usage rates of the product. Subsequently, they presented a two-dimensional model of product failure through conditional inference. Davis [6], building on the model of Lawless and colleagues [5], introduced a simpler approach to analyzing two-dimensional warranty failure data for automobiles. In this approach, they first estimated the marginal density function of the time to product failure and then extracted the conditional function of the customer's usage rate, followed by conditional inference. Majeske and Herrin [7] also presented techniques and analyses such as graphical representation of warranty failure data, estimating the failure rate function, maximum likelihood ratio test, and goodness-of-fit test for predicting the failure process of products with two-dimensional warranties. They utilized this model to predict future product failures.

In another study by Majeske [8], employing a heterogeneous Poisson process, a model was presented to predict requests for two-dimensional warranty services in terms of time and product usage. Rai and Singh [9] examined warranty data for situations where customers rush to the manufacturer for services towards the end of the warranty periods. They then proposed a model to extract the product failure process at the component level using this type of data. Rai [10], aiming to analyze two-dimensional warranty failure data, recommended plotting the product failure rate graph to gain a proper understanding of noise data and studied how to estimate reliability and factors influencing warranty cost reduction. Chukova and colleagues [11], reviewing research in the warranty data analysis domain, studied the models proposed in this field, critically assessed and categorized these studies in the form of a review article. Concurrently, with the above research, Wu [12] also conducted a review and critique of the literature on warranty data analysis. Akhtar and Karim [13], for the analysis of failure data of automobile components during the basic warranty period, presented a model based on time. In this model, important failure modes of components were initially identified based on the Pareto chart and preliminary analysis, and then non-parametric analysis was used to extract the cumulative distribution function of the time to failure.

Summit [14] also investigated models predicting warranty costs over the course of the basic warranty period for automobiles. Kwang-Wook and colleagues [15] predicted requests for warranty services for automobiles using fuzzy-neural networks. In another article, Rai and Singh [16] utilized Wavelet transformations and neural networks to predict failures of products under two-dimensional warranties.

It is evident that a considerable body of research has focused on predicting the failure process of products with two-dimensional warranties. In this article, the failure process of mechanical components of a car operating in Iran is extracted using failure data. It is worth noting that the modeling process and extraction of failures are based on the approach introduced by Lawless and colleagues [5], and efforts have been made to consider both scientific and practical aspects in such estimations. Given the complexity of factors affecting the product failure process, it is unrealistic to expect precise predictions from such models. However, with a realistic perspective, these models can be used to better understand the product failure process and subsequently estimate the associated costs.

The following sections of the article will be presented as follows. In the next section, the process of estimating failures will be explained. Subsequently, in the numerical example section, graphical representation of real data will

be provided, and the process introduced in the previous section will be implemented on the data. The analysis of these data and the presentation of conclusions will conclude the present article.

## 2. APPROACH TO EXTRACTING THE FAILURE PROCESS

For a new product with a two-dimensional base warranty, consider (W, U) as constraints on time and product usage. This means that if the product's lifespan exceeds W or the usage exceeds U, the base warranty expires. To estimate the failure process of the product based on time to first failure and product usage, assume there are n data points related to the first failure during the base warranty period, where  $(x_i, u_i)$  for  $i=1,2,\dots,n$ , and  $x_i$  is the time to the first failure, and  $u_i$  is the product usage at the moment of the first failure for the  $i$ th product. In this case, the steps for extracting the probability distribution of product failures in terms of time and usage until the first failure, using the marginal approach, will be as follows:

Step 1: First, calculate the customer usage rate for the  $i$ th product at the moment of failure as follows:  $r_i = u_i / x_i$

Step 2: Let R be the customer usage rate for the product, which is a random variable with the probability density function  $g(r)$ . By fitting probability distributions to the data of customer usage rates for the products  $(r_i, i=1, \dots, n)$  and conducting a goodness-of-fit test, the distribution governing R is extracted. If it is not possible to find a parametric distribution for it, non-parametric estimation can be used to describe the customer usage rate. For further details, refer to the reference.[5]

Step 3: Separate the data for the time to failure of products with customer usage rates close to the nominal rate  $R=r_0$ . By fitting probability distributions to these data points, the conditional probability distribution of time to failure for the product under the nominal usage rate ( $X_{r_0}$ ) is extracted. Let  $f(x; \alpha_0, \beta)$  be the conditional probability density function for the time to failure of the product, where  $\alpha_0$  is the scale parameter, and  $\beta$  is the shape parameter of the distribution.

Step 4: Using the Accelerated Failure Time (AFT) model, extract the effect of changes in the customer usage rate of the product on the conditional time to the first failure of the product (in terms of the parameter  $\gamma$ ) [17]. According to this approach, we have:

$$\frac{X_r}{X_{r_0}} = \left(\frac{r_0}{r}\right)^\gamma \tag{1}$$

where  $X_r$  is the random variable for the conditional time to the first failure of the product under the usage rate  $R=r$ , and  $\gamma \geq 1$  is the AFT parameter. Using this approach, the scale parameter of the distribution of  $X_r$ , denoted by  $\alpha(r)$ , is calculated from the following relationship [17].

$$\alpha(r) = \alpha_0 \left(\frac{r_0}{r}\right)^\gamma \tag{2}$$

Therefore, by estimating  $\alpha(r)$ , the probability distribution function of  $X_r$  will be  $f(x; \alpha(r), \beta)$ . In other words, with changes in the customer's usage rate, the type of distribution and the shape parameter of the time to the first conditional failure remain constant, and only the scale parameter changes according to the equation (2).

Step 5: By making the time to the first failure unconditional on the random variable of the customer's usage rate, it is possible to calculate the two-dimensional failure distribution function.

In conclusion, with the determination of the two-dimensional failure distribution function, it is possible to use this function to calculate the expected number of failures during the two-dimensional basic warranty period. However, it should be noted that the estimation of this function is based on data from products that have experienced failure at least once during the basic warranty period. This means that products that have not failed during the warranty period are not considered in these calculations. Therefore, the estimated failure distribution is significantly

more pessimistic compared to the actual distribution of failures for all products, and it can be expected that the total number of failures in all products is much less than the quantity estimated by this distribution. For a more accurate estimation of the actual failure distribution of the product, one can refer to the reference [17].

Additionally, it is essential to consider that warranty failure data are right-censored, meaning that due to the heavy usage rate of customers, the warranty expiration time may be earlier than  $W$ . In this case, the recorded failures during the warranty period will not be applicable to product failures in the time interval  $(0, W)$ . This consideration applies similarly to failures based on the product's usage level. Therefore, to account for the characteristics of this type of data in the estimation of distributions, attention must be paid to how to estimate distributions under censored data. For further information on this matter, one can refer to the source [12].

Assuming that the type of repair during product failure is minimal, the number of failures during the two-dimensional base warranty period will follow a non-homogeneous Poisson process. The intensity function will be equal to the failure rate of the random variable time to the first failure of the product, denoted by  $X_r$  [17]. Let  $h(x|r)$  be the failure rate function of the random variable  $X_r$ . The expected number of product failures during the two-dimensional base warranty period will be as follows:

$$E(N_f(W, U)) = \int_0^\infty \int_0^W h(x|r)g(r)dxdr \tag{3}$$

With the determined failure distribution function, the expected cost of failures during the two-dimensional base warranty period can be calculated. For this purpose, it is sufficient to multiply the expected number of failures during the warranty period by the expected cost of repair for each failure. If the cost of repairing a failure occurring at moment  $x_j$  for a product under the usage rate  $r_j$  depends on the time of failure and the product's performance level at the moment of failure, then the cost can be calculated using the following equation:

$$C(x_j, r_j) = c_0 + c_1(x_j)^a(r_j)^b \tag{4}$$

Where,  $a, b, c_0$ , and  $c_1$  are parameters of the cost function that can be estimated by fitting the equation to real data. Considering such a cost function, the expected cost of product failures during the base warranty period will be as follows:

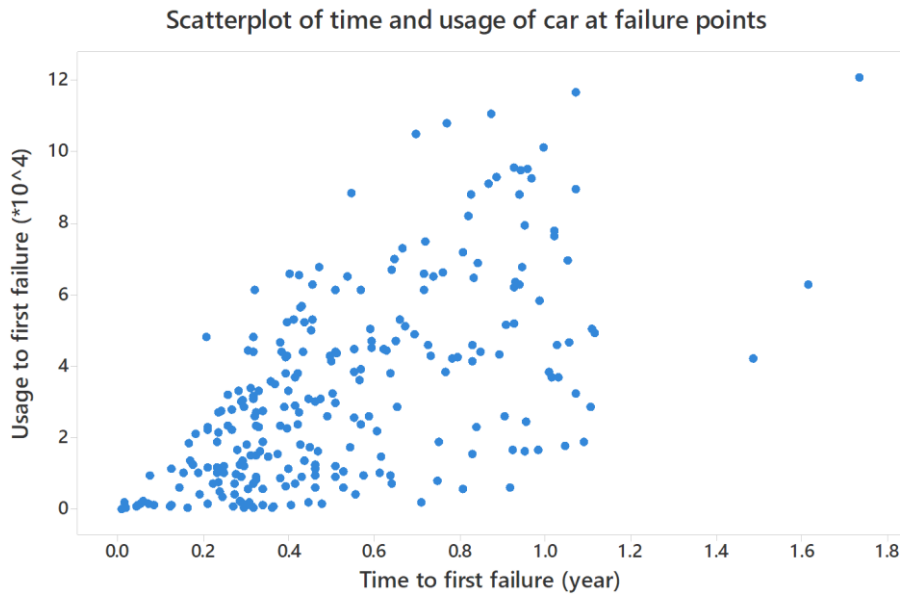
$$E(C_f(W, U)) = \int_0^\infty \int_0^W C(x, r)h(x|r)g(r)dxdr \tag{5}$$

In the following section, the two-dimensional failure distribution of the mechanical components of a working car in Iran is estimated using the failure data.

### 3. CASE STUDY: A WORKING CAR IN IRAN

For a domestically produced car in Iran, two-dimensional warranty failure data have been recorded by service representatives throughout the base warranty period. The warranty period for this car is defined as  $W=3$  years, and  $U=20$  ( $\times 10^4$ ) kilometers, representing the maximum time and mileage thresholds. The warranty for the car expires if it surpasses any of these limitations. There is a total of  $n=252$  recorded failure data for the mechanical components of this car. For each recorded failure, the time of occurrence is noted in years from the delivery of the car to the customer, along with the distance traveled by the car in tens of thousands of kilometers and the identified failed component.

To better understand the relationship between the time to failure and the usage of the product at the moment of failure, a scatter plot is drawn. Figure (1) illustrates this scatter plot for the failure data of mechanical components.



**Fig. 1.** Scatter Plot of Time and Distance Traveled to the First Failure of a Working Car in the Base Warranty Period

As observed in Figure (1), a positive correlation is evident between the time to the first failure and the distance traveled by the car, indicating the logical validity of the assumption of the existence of the relationship  $U=RX$ .

With these field data and the implementation of the introduced steps in the previous section, the two-dimensional failure distribution of the product is extracted. By fitting various distributions to the customer usage data using Minitab software and comparing the Anderson-Darling statistic (Adj), it is observed that the Weibull distribution provides the best fit to the data. The characteristics of the fitted Weibull distribution are shown in Figure (2). According to the results, R follows the Weibull distribution with parameters  $R \sim \text{Weibull}(\alpha_R=8.8963, \beta_R=1.4033)$ .

Furthermore, using MATLAB software, the cumulative distribution function curve of the fitted Weibull distribution is compared with the cumulative distribution of the actual data in Figure (3).

Subsequently, considering the average customer usage rate as the nominal usage rate ( $r_0=6.28 \times 10^4$  kilometers), the conditional distribution of time to failure given the nominal usage rate is fitted. The results of this fitting also support the idea that the Weibull distribution can provide a better fit to the data of time to the first failure of the product. The characteristics of the time to failure distribution are  $X_{(r_0)} \sim \text{Weibull}(\alpha_0=0.5903, \beta=1.8098)$ , and its specifications are depicted in Figure (4).

Estimation Method: Maximum Likelihood				
Distribution: Weibull				
<b>Parameter Estimates</b>				
Parameter	Estimate	Standard Error	95.0% Normal CI	
			Lower	Upper
Shape	1.40334	0.0727707	1.26772	1.55347
Scale	6.89637	0.323904	6.28988	7.56135
Log-Likelihood = -698.564				
<b>Goodness-of-Fit</b>				
Anderson-Darling				
(Adjusted)				
2.199				

Fig. 2. Results of Fitting Weibull Distribution to Customer Usage Data (Minitab)

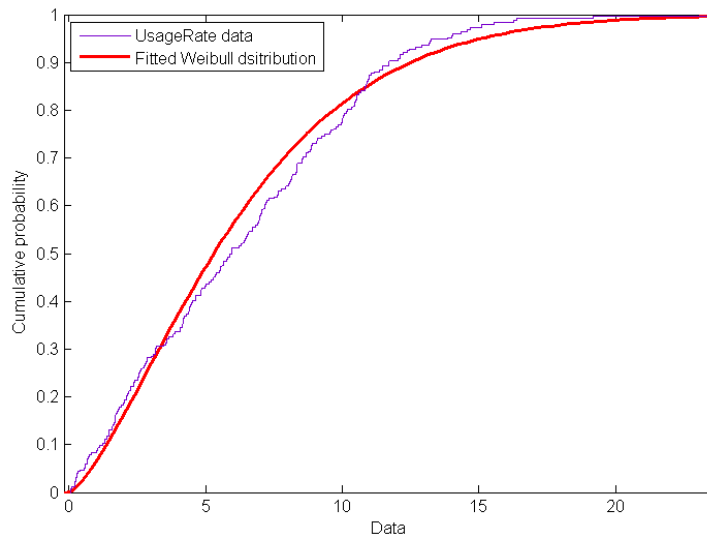


Fig. 3. Comparison of Cumulative Distribution Function of Fitted Weibull with Actual Customer Usage Data (MATLAB)

Estimation Method: Maximum Likelihood				
Distribution: Weibull				
<b>Parameter Estimates</b>				
		Standard	95.0% Normal CI	
Parameter	Estimate	Error	Lower	Upper
Shape	1.80985	0.0882969	1.64481	1.99146
Scale	0.590298	0.0216197	0.549410	0.634230
Log-Likelihood = -34.748				
<b>Goodness-of-Fit</b>				
Anderson-Darling				
(Adjusted)				
1.482				

Fig. 4. Results of Fitting Weibull Distribution to Time to First Failure Data (Minitab)

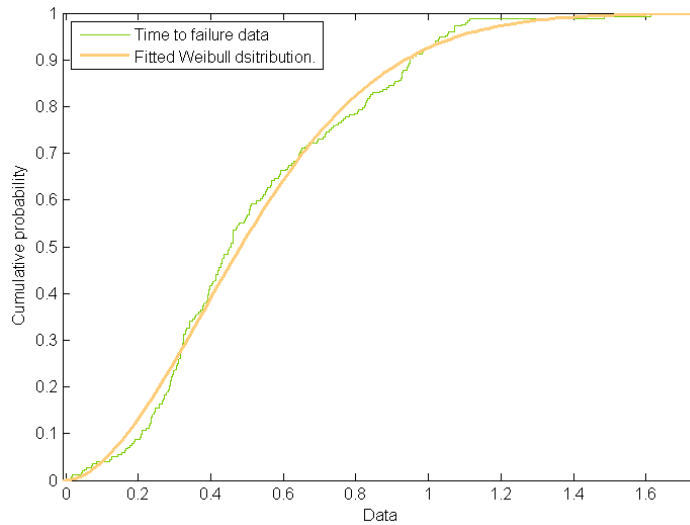


Fig. 5. Comparison of Cumulative Distribution Function of Fitted Weibull with Actual Time to First Failure Data (MATLAB)

The distribution of product failures over time, given the customer usage rate

R=r, can be expressed as follows:

$$\int_0^{\infty} \beta(\alpha(r))^{-\beta} x^{\beta-1} \times \frac{\beta_R}{\alpha_R} \left(\frac{r}{\alpha_R}\right)^{\beta_R-1} e^{-\left(\frac{r}{\alpha_R}\right)^{\beta_R}} dr \tag{6}$$

$$E(N_f(W = 3, U = 20)) = \int_0^3 \int_0^{\infty} \beta(\alpha(r))^{-\beta} x^{\beta-1} \times \frac{\beta_R}{\alpha_R} \left(\frac{r}{\alpha_R}\right)^{\beta_R-1} e^{-\left(\frac{r}{\alpha_R}\right)^{\beta_R}} dr dx \tag{7}$$

It should be noted that in this case study, due to the lack of access to supplementary data, the parameter value of the AFT model was assumed to be  $\gamma=1.05$ . This assumption was made while the actual value should be estimated using field data. Considering the extracted distributions and the assumptions made, the expected number of failures

for the examined car during the base warranty period is estimated using the equation (7) as  $E(N_f(W=3, U=20))=12.96$ . Examining the number of failures during the base warranty period suggests that the estimated number of failures appears pessimistic, while field observations indicate significantly fewer failures. In explaining this difference, it should be noted that, as mentioned in the previous section, the extracted failure distribution represents products that have failed at least once during the base warranty period, and products that have never failed during this period are not considered in these calculations. Therefore, for an accurate estimation of the failure process for all products, the total number of products sold under warranty should be determined, and by applying this number, the failure process for all products should be adjusted. By performing such adjustments, it can be expected that the estimated number of product failures will be closer to the actual value.

In this case study, due to the unclear number of products sold during the data collection period, these adjustments were not made. For more information on how to adjust the failure distribution function and correct it based on the total number of products, you can refer to the reference [12].

In estimating warranty costs for the case study, due to the lack of access to field repair costs for each failure, parameter values for costs are assumed as follows:  $c_0=10$ ,  $c_1=40$ ,  $a=1.18$ , and  $b=1.8$ . Then, by solving equation (5), the expected cost of failures during the base warranty period is calculated as  $E(C_f(3,20))=34481$ .

It is observed that using the derived relationships allows for the calculation of the number of failures and the expected cost. However, it should be noted that for a comprehensive understanding of failures and costs, focusing on the average value alone is not sufficient. Instead, it is necessary to consider the range of potential failures and the associated costs to effectively manage the risks of failures and associated expenses.

#### **4. CONCLUSIONS**

In this article, data on failures of the mechanical components of an Iranian-made utility vehicle were collected over the base warranty period for 252 products. The failure process of these products was then extracted based on the time to the first failure and the customer's usage rate of the product. To achieve this, the Weibull distribution was initially extracted as the distribution of the customer's usage rate, and for the nominal usage rate, the Weibull distribution of time to the first failure was estimated. By deriving mathematical equations governing the product failure process, the expected number of product failures was estimated. Subsequently, assuming that the cost of each failure depends on the time of failure and the customer's usage rate of the product, the expected cost of the product during the base warranty period was calculated for the assumed parameters of the failure cost function.

The actions and calculations performed in this article are based on available information, but to make the estimates more realistic and accurate, attention should be paid to the following points:

In estimating failures, only data from products that have failed at least once during the base warranty period have been used, leading to a pessimistic estimate of the failure process. Therefore, adjustments are necessary to adjust the failure process and extract the failure process for all products, considering the total number of warranty-covered products.

To estimate the time to the first failure for the nominal usage rate, a sufficient number of products that have been under the nominal usage rate should be available to more accurately estimate the probability distributions governing them. The effect of changes in the customer's usage rate on the time to the first failure should be accurately estimated using the Accelerated Failure Time (AFT) method, as the estimated value for the AFT parameter can significantly impact the acceleration of the failure time and the inaccurate estimation of the number of failures during the warranty period.

For accurate estimation of repair costs, it is recommended to use field data. Otherwise, relying solely on the average cost of each repair can provide an approximate and supportive estimate. In estimating the failure process, due to the nature of warranty data, which is referred to as right-censored data, attention should be paid to the effect of censoring on the failure process. For this purpose, research reported in this area, such as [12], can be consulted.

In conclusion, working with real failure data to extract patterns governing the data is an enjoyable and value-creating process that can contribute to a correct understanding of the product failure process, the performance of production departments, suppliers, part quality, service delivery, and associated cost management. However, it should be noted that the correct extraction of this information requires the proper design and collection of the necessary data, precise attention to the scientific foundations of data processing, mastery of the nature of the data, and how to analyze them, and superficial processing of the data should be avoided. Hopefully, researchers in this field will pay attention to these aspects in future research and provide results that are much more reliable.

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## **Transparency Statement**

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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## **Declaration of Interest**

The authors declare that they have no competing interests.

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