Identifying Durability Failure Parts using 24 Months-In-Service Data: A Case-Based Empirical Study from an Automobile Manufacturer in India

Naveen Kumar K, **Maheshwar Pratap**

Abstract: This paper analyses the warranty claims data to identify faulty parts contributing to increasing failure using Weibull Analysis, in the automobile industry. Unlike studies in the past, this study uses 24 month service data to investigate the cause of failure due to faulty parts.Usually, the forecasting of the part failure is done for the 3 months in service (MIS) data and the automobile manufacturers use this parameter to set Key Performance Indicators (KPI) for quality improvement among design engineers. The KPI set using 3MIS data is used to determine 12 MIS and 24MIS KPIs. The period used in the development of KPIs affects the number of failed parts to be selected for improvement. As the monitoring period of countermeasure takes long durations, the repetitive failures added in data during the monitoring period, make the analysis complicated. Also, the seasonal pattern of failures cannot be addressed using 3MIS data. By increasing the analysis period to 24MIS, this paper finds evidence that increase in MIS leads to the identification of faulty parts that are causing repeated failures. The scope of the study extends towardsthe detection of new issues and towards monitoringthe effectiveness of existing countermeasures.This reduces warranty costs for the manufacturer and provides time to develop appropriate countermeasures along with increased monitoring period of failure parts leading to durability quality improvement.

Keywords: Warranty claims forecasting, Warranty Analysis,Weibull Analysis, Part Drability.

I. INTRODUCTION

The Japan-based multinational automobile manufacturer has its production plant in India. The company manufactures and sells cars for use in India and also exported to other countries. Warranty service is the key selling tool for automakers and they know the importance of warranties in customer retention. This auto manufacturer also provides two years warranty/100000 Kms for their cars to Indian customers. One reason that the warranty period is limited to 2 years /100000 Kmis that of the cost burden.

The company aims at improving the quality of the parts to ensure reduced warranty costs and also to provide longer warranty to retain customers. The company uses its warranty claims and sold data and calculates MIS% (incident ratio) which is MIS ratio = Number of claims / Number of vehicles in service

Revised Manuscript Received on 8 February 2019.

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This is calculated for 3months in service period for each month. MIS commitment is set for every quarter and the same is forecasted for 12MIS and 24MIS commitments.

Using the available data, the analysis of the durability quality improvement process is carried out. It is found that the current method utilizing 3 months in service warranty data was revealing only the early stage failures. The commitment set based on this result only focuses on the initial failure parts and does the subsequent quarterly analysis. An alternative method was suggested which could reveal the increasing failures over time which upon durability quality improvement might reduce the number of warranty claims and thereby the costs associated with it. Thus this paper focuses on identifying the automobile part's increasing failure for durability quality improvement by conducting Weibull analysis on the warranty and claims data for the actual warranty period. This enables the company to reduce its spending on warranty services and also can provide customers with an extended warranty with quality parts.

II. LITERATURE REVIEW

The identification of durability of the parts depends on various factors like the data used for the analysis, the methodology followed in the company and parameters considered in the analysis. Thus the study considered various literature relevant to the study to understand those factors.

A. Weibull Distribution

Weibull distribution was first described by a Swedish mathematician Waloddi Weibull in 1951. It was first identified by Fréchet in 1927. [1] Weibull distribution is a probability density function of a Weibull random variable which gives the distribution of the failure population in proportion to the power of time. Its shape parameter provides the information on failure rate. Its shape parameter for say, $k<1$, indicates decreasing failure while $k>1$, indicates an increasing failure. Weibull distribution plot shows a bathtub shaped curve of failure types. The understanding about two-parameter and three-parameter Weibull distribution is known from [2] thesis on stress on the Weibull parameter determination for failure analysis. The data for failure probability rate may not fit both the types of Weibull distribution.

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Discussion about the product reliability in business processes is said in [3] and cited the different classes of failures and explained about the early-stage, random and systematic wear-out failures. Most mechanical products showdegradation over time and early-stage failures or early wear-out failures shows some discrete reliability and quality behavior and is expected to be occurred during manufacturing or due to internal flaws. The Total Time on Test (TTT) plot of identifying hazard rate by bathtub – shaped curve [4] earlier which also resembles the plot of Weibull distribution. The author discussed more about the types of hazards. This formed the basis for understanding the types of failures and it gives the better understanding of the bathtub curve in Weibull plots. [5]shows the investigation of life distributions of any product by bathtub distribution model in comparison with the exponentiality (constant hazard rate) for the same period to understand the variance in them. Monte Carlo simulation for the comparison is used. This paper provides insights on performing bathtub distribution in Monte Carlo simulation and the plot is obtained. Weibull analysis is found to be more accurate than exponential method.

B. Weibull Analysis application in Automotive Sector:

The survival analysis on warranty and claims data provides insights about the failure types and also warranty cost prediction can be made. Thus the warranty data provides major business insights. Weibull distribution is found to be commonly used in warranty analysis by automakers. The reasons for the choice of Weibull analysis in the automobile industry are reviewed in this section starting with the understanding of warranty claims processing in the industry followed by the need for Weibull analysis. The analysis of the warranty process flow analysis in the automobile industry can be understood from [6]. He proposes the importance of warranty in the automobile industry which it uses to retain customers. This paper presents the role of vehicle manufacturer in warranty and the process involved. The longer the warranty the company desires to provide its customers, the higher the durability quality should be, as the cost of the warranty to the company is a burden. Data analysis in warranty process and the lead time in detection to countermeasure action are essential in warranty process in automobile industry. In explaining the various methods of stating reliability and maintenance [7], has proposed the role of warranties in understanding the reliability of a product. The method of improving the product quality or providing a new product relies on the feedback from the customers. He also has mentioned the delay in warranty claims data entered from the date of failure. But with the single software system handling the data flow of the company with its distributors and service centres, there wasn't any delay between the incident time and the reporting. The experimental analysis of how the Weibull distribution model can be applied to forecast the failure probability or risk possibility in automobile industry using available defect claims is shown in [8]. This paper has justified the utilization of Weibull distribution for failure prediction by conducting the fit test on actual after-sale service data. This result was found satisfying to conduct Weibull distribution analysis for our proposed study. Similarly [9] presented a significant proof on using Weibull distribution on warranty data to predict the future warranty returns. The bathtub curve realized in this model distinctly shows the early stage, constant and wear-out failures. The past warranty claims analysis and its impact on the market value of the current vehicle and the new vehicle to be sold is made clear in this paper. The business decisions related the financial and marketing considerations are also based on this analysis. In [10] Maurizio proposed reliability inference based on past data in which the use of probability density function (Pdf) on the past failure information collected through various context could support the effectiveness of the improvement measures to be taken on the new product to understand its reliability. The product life is measured by the number of kilometres ran and the duration it took. Also in [11] discussed the importance of utilizing the warranty and claims data to understand the product quality and its reliability. This paper reviews various analyses were done on warranty claims data for prediction by emphasizing on the models and methodologies used. The early detection of reliability problems could help in identifying unexpected quality problems. The data used in this paper is the warranty claims data separated in periods such as 0–30 days, 31-60days and include sales date and sales volume. The understanding of why Kaplan Meier estimator is not suitable for warranty data analysis due to mileage restriction is discussed in [12]. Not all vehicles get failed during the mileage limit and hence the data for estimation becomes a risk. The reliance on the failure date is given more important and the customer may delay in reporting the issue might affect the analysis. In the dataset taken for our study ignores such factor as the failure date is concerned with the date of warranty claim and moreover failure rate is computed against mileage. There are methods to assess the impact of mileage or time warranty limits on the warranty claims count and the cost associated [13]. The analysis used on the dataset for this study is Weibull distribution. Weibull distribution is used in this paper to fetch the decreasing, constant and increasing failure rates from the given data. The parameters of Weibull distribution is well discussed in this paper with respect to the different failure phases. The Kaplan-Meier life curve analysis and Weibull distribution with two-parameter analysis on warranty data and compared with the known results to compare their accuracy in prediction [14]. It is found that the failure rate predicted by the Weibull distribution method agrees well with the known result. But the plot of cumulative failure against the mileage was found to be more realistic from the analysis. It has taken into account the data scenario in which a car might be kept without using for a long time. So a Weibull plot with mileage factor could give a more fitting result. Life distribution method on predicting the potential warranty issues for different caseswas discussed in [15]. The author suggested using early warranty data for both time and distance based analysis. The experiment was conducted for different time periods and distances and plotted the Weibull slope describing the three classes of failures.

This paper discussed the on how to utilize the life distribution analysis for predicting potential warranty claims in the automobile industry and distinctly predicting the nature of the failure. An Australian car manufacturer's warranty claims data for analysingthe reliability of the parts which later is used to forecast warranty costs [16]. The paper discusses various analysis models for part reliability and identified Weibull distribution as the most accurate for modelling and also the need for verification of field data gathered. The various models were used and checked against the warranty costs. The proposed study proved that the Weibull model is accurate in predicting the estimated costs when ß estimates lie outside the confidence interval.[17] conducted a study to estimate the failure distributions from automobile warranty data when both time and usage, which in the case of an automobile is mileage limits, influence the failure rates. He proposed models to analyse the warranty claims along with the mileage data based on real data. Hazard function was used to represent the mileage accumulation and mileage at the time of repair and its corresponding time, which is the age of the car, is noted. Weibull distribution of the warranty data with both time and mileage as a factor is conducted to estimate the reliability of the vehicle.

C. Applications of Weibull distribution in survival analysis in other industries

In [18] the several approaches for survival forecasting is discussed by the authors on patients with ovarian carcinoma and major importance is given to the Weibull distribution analysis and lognormal analysis on the data. Also [19] shows that Weibull distribution is used in medical follow-up data to check the adequacy to describe posterior distribution. Even in the statistical analysis of complex medical devices failure [20],Weibull distribution is considered in finding the failure types and could provide information for developing optimization models for maintenance. In reliability engineering, the failures of the components were identified using the time-distribution of the failure population and Weibull distribution is widely used [21] From the literature reviews, the proposed study observes that the Weibull distribution is a better fitting model for reliability study of probabilistic failures and the larger data is needed for realizing the increasing failures which put forth the longer period of data and mileage as usage factor to be considered.

III. METHODOLOGY

A detailed study on the analysis of warranty and claims data for the parts quality improvement carried out in the company is conducted to understand the issue with identifying the durability quality failure parts. The warranty and claims data of the company for the past 2 years on a particular model is taken for the study. For the analysis purpose, one part of a vehicle model is considered for the study. The warranty claims data of period starting from January 2016 to May 2016 is considered for the study for 3 MIS period and the data for 24 MIS period extends till March 2018. The 0^{th} month (January 2016) is considered to be the production month and its warranty is before the sale (warranty in the logistics process and during inventory). An extra month is considered in the study as process delay period. The total number of cars of this particular model sold during the 24 month period is 61699and the claims data on total during the same period is 1870 claims. The data is restricted to Indian market region only for the sake of the study. Weibull type hazard analysis [1] is used to analyse the warranty data for the parts failure rate. Weibull distribution gives the part failure rate which is a better choice for predicting future failure trends. The Weibull with three parameter equation for failure rate is given by

$$f(t) = \frac{m}{\alpha}\frac{(x-\mu)^{(m-1)}}{\alpha}exp^{(-((\frac{x-\mu}{\alpha})^{m})}$$

f(t) is the failure probability over time (t) with t as exponential time or the distance as mileage in kilometres. m is the slope of the plot and shape parameter and α is the scale parameter which describes the range of variable lifetime and μ is the location parameter which conveys that failure occurred after time, μ.ηis the characteristic life of the part, which means the time at which 63.2% of the population has failed. Weibull analysis is conducted on the warranty and claims data of the 3 months in service period of a model and the parameters are observed. For the same model, 24 months in service data starting from the same month as 3 months in service Weibull analysis is conducted and the parameters are noted. The cumulative failure rate is plotted against the mileage in Kms.

IV. ANALYSIS AND INTERPRETATION

Weibull analysis is conducted to get the Weibull distribution plot using the Reliability Support System software on the 24MIS data and the result is observed. First, the Incident rate against the production months is plotted for the vehicles that are less than 36 months in service. In 2016, the incident rate for 24 months in service vehicles is found high at around 0.70%, while the 3 months in service incident rate is very less.

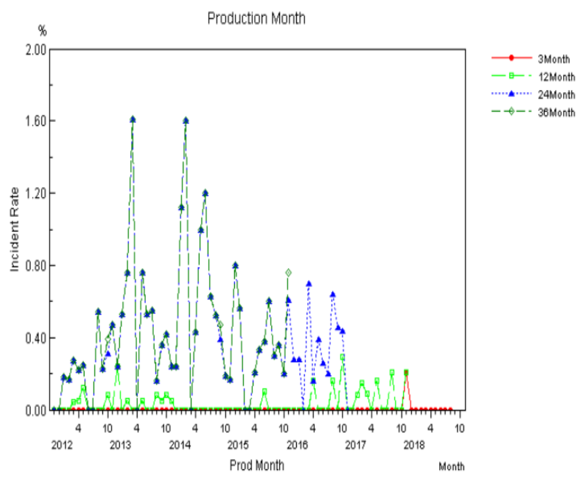

Fig.1 Incident rate vs. production month for the period from 2012 to 2018

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This leaves us with the fact that the 3 MIS incident rate is not enough to predict the failure rates. Also found is that the 24 months in service vehicle claims are consistently high. Therefore to predict failure rate from the period after October 2016, Weibull analysis is conducted for the 24 months in service claims data.

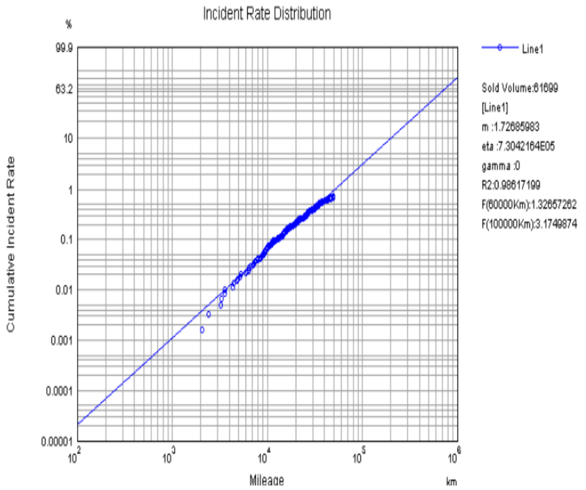

Fig.2. Weibull plot showing cumulative failure rate against mileage (in Kms) m=1.726, a total of 61699 vehicles were sold during that period. R^2= 0.986. Characteristic life parameter η= 7.30

In Fig.1 the contribution rate, r^2 is 0.986 indicates that the data is 98.6% reliable and contributed to the Weibull plot. The plot shows the Weibull slope m value 1.726 which greater than 1 (a value lesser than 1 represents decreasing failure rate) showing the reliability projection is too sound to be noted and immediate action is needed. Thus this part is found to have a high increasing failure rate. Further,from a vehicle's multiple parts claims data, the parts having increasing failure can be predicted from the reliability support system software which was earlier used to predict from 3MIS data. When doing so, the slope value is set greater than 1 to isolate the increasing failure parts. These parts can then be sort and decided for durable quality improvement based on other factors.

V. DISCUSSION

The importance of warranty and claims data for understanding various insights and its role in business aspects is studied. The key findings were that though they changed from their earlier method, 'priority list', which used 2 weeks data, the company adopted 3MIS data for identifying potential durability items which identified only initial failures every quarter and failed to identify the actual durability failure parts. Though incident rate results based on 3MIS data analysed every quarter has let the automakers to make quick actions on the failure, the MIS commitments based on 3MIS data set for 12 and 24 months were misleading in terms of durability improvement and also were neverable to meet. From the analysis of 24 months in service data, Failure rate F(t), at t = 100000 Kms mileage is predicted at 30% which means 30% of the sold vehicles are expected to get failed at mileage t. This insight is important in taking market actions in a country like India, where the recall activity may anytime be made compulsory in the automobile sector by the Government. Thus monitoring of increasing failure will let the company take measures early and adopt in new vehicles. This automobile company which sets KPI based on Vehicle Dependability Study survey upon improving the durability of the vehicle can increase the rating in the respective segment.So the proposed study suggested utilizing 24 months in service data for identifying increasing failures. The experiment conducted on one of its vehicle using Weibull analysis revealed the actual increasing failure parts and this finding were different from the recent 3MIS result. This method also reduced the lead time in fetching defected parts which are identified when using 3months data where a number of defected parts is sometimes too less for conducting the investigation and to be fetched from across the country or sometimes have to wait for more claims to come. These findings were produced to the Quality Control team. The selection of major parts for durability quality improvement for that quarter from the result will be decided by the management based on other criteria.

VI. CONCLUSION

The multinational company has production plants in various other countries and methods adopted there were not taken into study. The study has been conducted with the available data and other information provided. This study focuses on the issue of parts adoption for durability quality improvement which directly one of the reasons for increasing warranty claims. The factors influencing the key metric for quality improvement adopted by the company is identified and analysed. There are other alternatives such as Kaplan Meier survival analysis, exponential based reliability modelling etc. as different tools to visualize but this method seems to be most relevant and widely accepted model for identifying the failure probability and does not have to alter the entire procedures. Also,the new methodology would involve new procedure adoption and training costs. As one application of this method, the company can now focus on improving the durability of the parts. A business decision of market activities such as recall can be made based on this analysis. As a fact, an increasing failure trend would invoke a bad customer experience. Moreover,the lead time in fetching the defected parts also have increased.

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