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Service Life Reliability Predictions for Heat Exchangers: a 9 years-Warranty Data Analysis

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Extended automotive warranty mandates present a critical challenge for Tier-1 suppliers who must navigate sparse downstream visibility and non-stationary field failure rates. This paper proposes a robust statistical framework for long-term warranty risk assessment, specifically addressing the data-gap between manufacturer shipments and vehicle-in-operation (VIO) exposure. We introduce a multi-stage methodology that integrates: (i) an exposure-alignment algorithm utilizing shipment-suspension synchronization, (ii) a clustering technique based on Parts Per Million (PPM) trend analysis to mitigate quality heterogeneity, (iii) a composite reliability modeling approach employing Weibull and Mixed-Weibull distributions.

The proposed approach is validated through an industrial case study involving automotive components, utilizing 0–6 years of matured warranty data and 7th–8th year immature claims to forecast warranty performance over an extended horizon from 3 to 15 years. The forecasted warranty returns demonstrate strong agreement with observed field data, with actual claims consistently falling within the 90% upper confidence limits. Incorporation of vehicle survivability via a scrappage-rate adjustment further enhances long-term forecast realism. The results confirm that the proposed framework effectively addresses industrial data constraints and provides a robust, practical solution for extended warranty provisioning and risk management in automotive applications.

Keywords: Extended Warranty, Mixed-Weibull, Warranty Risk Assessment, Scrappage-rate, PPM.

1. Introduction

Automotive warranty terms have traditionally been driven by market expectations, with product reliability serving as a supporting input in defining standard coverage limits. Conventional warranty periods are generally designed to terminate somewhere in the random failure phase of the product life cycle. In recent years, however, regulatory mandates and competitive market strategies in several regions have resulted in substantial warranty extensions, in some cases from 3 years or 36,000 miles to as long as 15 years or 150,000 miles. Such extensions significantly increase the exposure period and may encroach into the early wear-out phase or approach the end of the product's design life, thereby introducing considerable uncertainty in warranty return forecasting and cost provisioning.

Accurate warranty risk estimation under extended coverage remains a major challenge for automotive manufacturers and Tier-1 suppliers. Despite the fundamentally different risk profile, many organizations continue to rely on analytical approaches developed for standard warranty horizons. These practices often involve the indiscriminate application of two-parameter Weibull models, no segmentation of heterogeneous failure populations, and inadequate interpretation of non-linear failure trends. Consequently, concave, convex, or S-shaped behavior is frequently misrepresented, leading to model misspecification and forecasts that lack statistical and physical credibility.

Extended warranty analysis requires a deeper understanding of failure mechanisms and their temporal evolution. Products operating under diverse usage conditions and environments may follow different lifetime distributions, necessitating adaptive modeling strategies and validation using actual field data. This paper addresses these limitations by proposing a structured methodology that integrates failure behavior segmentation, appropriate lifetime distribution selection, and data-driven validation to improve warranty risk assessment under extended warranty conditions.

2. Automotive Warranty Risk Assessment: A Tier-1 Approach

From the perspective of Tier-1 suppliers, warranty risk assessment is further complicated by several industrial realities. First, warranty datasets often comprise heterogeneous quality populations, such as pre- and post-countermeasure production or mixed manufacturing conditions, resulting in distinct high-PPM and low-PPM failure groups. Second, many automotive components exhibit multiple failure modes, including early-life and wear-out failures, leading to multimodal lifetime distributions that cannot be adequately represented by a single parametric model. Third, Tier-1 suppliers typically deliver components to a primary Original Equipment Manufacture (OEM) plant, after which parts are distributed globally across multiple vehicle assembly plants and markets. Consequently, suppliers often have limited visibility into region-specific vehicle sales and usage, making it difficult to correctly align field claims with the corresponding exposure volumes. Finally, accurate warranty risk estimation critically depends on proper synchronization of failure data with delivery, usage, and suspension (censored) information.

In addition, component lifetime is influenced by several explanatory variables, including operating conditions, production periods, and quality improvements over time. Statistical lifetime models that incorporate such covariates, often through regression-based reliability frameworks, are therefore essential for meaningful warranty forecasting. As a result, data cleaning, validation, segmentation, and appropriate distribution selection become indispensable prerequisites for robust warranty analysis.

3. Methodology

Automotive warranty terms are generally defined in terms of time and/or mileage, whichever occurs first, and are treated by manufacturers as the maximum coverage limitation. To analyze warranty data, estimate product lifetime, and monitor warranty performance, various methodologies have been proposed by automotive manufacturers and researchers, including day-based, month-based, and mileage-based approaches. In this study, the Month-In-Service (MIS) methodology is adopted, as it provides a consistent and practical framework for warranty risk assessment across different markets and usage conditions.

3.1. *Warranty Data Navigation and Preparation*

In practice, manufacturers receive large volumes of field warranty data, much of which is not directly usable for warranty risk assessment. Therefore, a structured data navigation process is required, as illustrated in Figure 1. The claims dataset is systematically cleaned by removing duplicate records and excluding secondary and subsequent repair claims. In this study, only first-repair claims are considered, since tracking exposure volume for second or later repairs is often challenging for manufacturers due to limited visibility of parts delivery and other operational constraints.

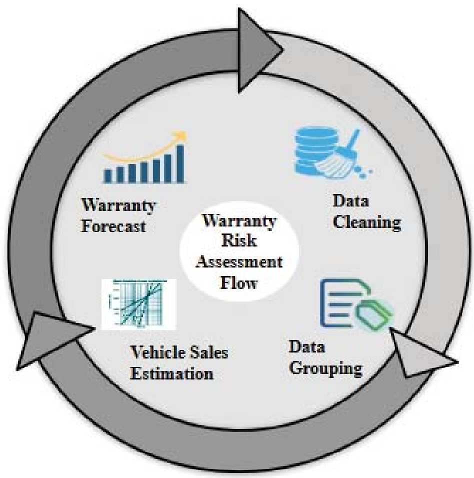

Fig. 1. Warranty Risk Assessment Flow

Missing or incomplete date information is reconstructed where feasible, and erroneous, inconsistent, or inaccurate records are removed to ensure data quality and reliability. The cleaned claims data are then organized into categories or clusters based on shared attributes to facilitate further analysis. A similar cleaning and grouping process is applied to parts delivery volume data,

Claim ID	VIN	Customer Part Number	Vehicle Manufacturing Date	Repair Date	Vehicle In Service Date	Mileage	Cost of Repair	MIS
12345	123ABCDEF1	123456789	10-11-2015	02-10-2017	07-12-2015	108444	1000	22
12345	123ABCDEF2	123456789	27-01-2016	10-10-2017	16-02-2016	39901	1000	20
12345	123ABCDEF3	123456789	02-11-2015	30-01-2020	22-11-2015	137654	1000	51
12345	123ABCDEF4	123456789	08-09-2015	13-10-2017	29-11-2015	148683	1000	23
12345	123ABCDEF5	123456789	15-12-2015	31-10-2017	23-01-2016	62629	1000	22
12345	123ABCDEF6	123456789	02-11-2015	10-11-2017	05-12-2015	75192	1000	24
12345	123ABCDEF7	123456789	21-09-2015	15-11-2017	15-10-2015	114235	1000	25
12345	123ABCDEF8	123456789	09-11-2015	09-11-2017	12-12-2015	75754	1000	23

Fig. 2. Cleaned Warranty Claims Data (not real values)

Tier-1 Supplier Sales Month	Tier-1 Supplier Sales Quantity
01-08-2015	2164
01-09-2015	2813
01-10-2015	2396
01-11-2015	855
01-01-2016	1763
01-02-2016	1710
01-03-2016	1890
01-04-2016	4140

Fig. 3. Parts Delivery Volume Data (not real values)

which are aggregated on a monthly basis. After these steps, the processed (cleaned) warranty claims and corresponding delivery volumes form a structured dataset, as shown in Figure 2 and 3.

3.2. *Vehicle Sales Distribution Estimation*

Vehicles are not necessarily sold to end users immediately after leaving the OEM plant. Consequently, manufacturers must estimate the vehicle sales distribution to correctly represent warranty exposure. The storage time (time between vehicle production and sales) is calculated for each claim, and the parameters of the vehicle sales distribution model are estimated using commercial reliability software (Weibull++ by ReliaSoft). The estimated sales distribution parameters are applied to the actual parts delivery volume using a traditional Nevada chart approach to derive the vehicle sales distribution for each month. This step enables the conversion of shipment volume into effective in-service exposure volume.

3.3. *Alignment of Claims with Tier-1 Delivery Volume*

To further improve exposure accuracy, the shipping time between the Tier-1 supplier and the OEM is incorporated into the analysis. Warranty claims are aligned with the appropriate Tier-1 delivery month based on the shipping delay. For example, if the shipping time is 15 days and warranty claims correspond to vehicles manufactured in January and February, then claims occurring from January 16 to February 15 are associated with the Tier-1 supplier's January delivery volume. This approach ensures correct alignment between claims and exposure volume at the supplier level.

3.4. *Seasonal Effects in Warranty Modeling*

Seasonal effects play a critical role in automotive warranty data analysis, as variations in climate, road conditions, and customer usage patterns can influence component degradation and failure rates. While certain parts are designed for continuous, year-round operation, empirical warranty data often reveal seasonal fluctuations in failure occurrences. These fluctuations may arise from temperature extremes, humidity, road salinity, or seasonal driving intensity, and can differ significantly across geographic regions.

Ignoring such seasonality may distort life-distribution parameter estimation, leading to biased scale and shape parameters in Weibull models or mischaracterized variance in lognormal models. For example, clustering of failures in specific calendar months may artificially inflate early-life or wear-out behavior when analyzed purely on a time-based scale. Therefore, when statistically or visually identifiable seasonal patterns are present, seasonality should be explicitly accounted for prior to fitting life distributions. Incorporating seasonal adjustments improves model fidelity and enhances the accuracy of warranty return forecasts.

3.5. *Trend Analysis and Data Segmentation*

A PPM trend analysis using an Isochrone chart is performed based on the processed claims data after applying the shipping-time adjustment. The Isochrone chart (refer Figure 4) displays the sales month on the x-axis, PPM on the left y-axis, and

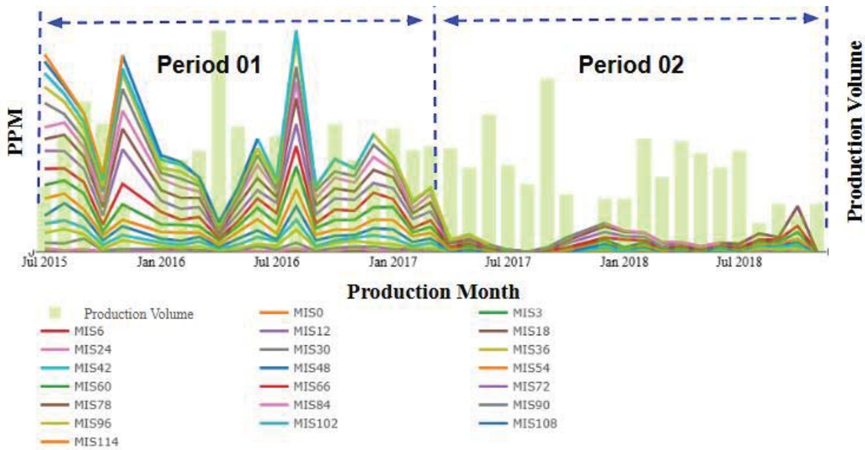

Fig. 4. Isochrone Chart for All Data

production volume on the right y-axis. Sales quantities are represented by bar charts, while trend lines indicate warranty repairs occurring at specific MIS intervals.

Trend lines are typically plotted at 0 MIS, 3 MIS, and subsequently at 6-MIS intervals up to the maximum warranty period. This visualization enables the identification of abnormal trends and potential quality shifts in specific production periods. Based on the Isochrone chart, distinct periods (e.g., Period 01, Period 02) are identified and isolated for detailed reliability analysis.

3.6. *Life Data Modeling and Warranty Forecasting*

Reliability data are generally classified into four types: complete data, left-censored data, right-censored data, and interval-censored data. In automotive warranty analysis, the data are predominantly right-censored, as only a portion of the population fails during the observation period while the remaining units continue to operate.

For each identified production period, the corresponding claims data and exposure volumes derived from the vehicle sales distribution Nevada table are used to construct right-censored life data tables (refer Table 2.2). These datasets are analyzed using HBK Reliasoft Weibull++ (version 22) software to identify the most appropriate lifetime distribution. Candidate models include the lognormal distribution, two-parameter Weibull, three-parameter Weibull, mixed-Weibull models with multiple subpopulations, and the exponential distribution.

The selected best-fit model is subsequently used to estimate failure probabilities, warranty returns, and associated costs. The application of the proposed methodology to an industrial automotive warranty dataset and the resulting warranty return estimates are presented in Section 4.

4. Industrial Case Study

This case study is based on an automotive Tier-1 supplier that delivered components to an OEM under a standard warranty coverage of 3 years or 36,000 miles, whichever occurred first. Due to regulatory changes in certain regions, the supplier was required to assess the impact of extending the warranty period to 15 years or 150,000 miles. At the time of analysis, the supplier had access to eight years of warranty claims data, of which approximately six years were considered saturated (ie, after this point, no further failures are expected), with a noticeable increase in claims observed during the seventh and eighth years of the warranty period.

The objective of this case study was to estimate warranty returns and provision requirements for the extended warranty period by leveraging the available field data. After data cleaning, validation, and grouping, an Isochrone chart was constructed using the processed warranty claims (refer Figure 4). The Isochrone chart clearly visualizes the relationship between warranty claims and Tier-1 production months,

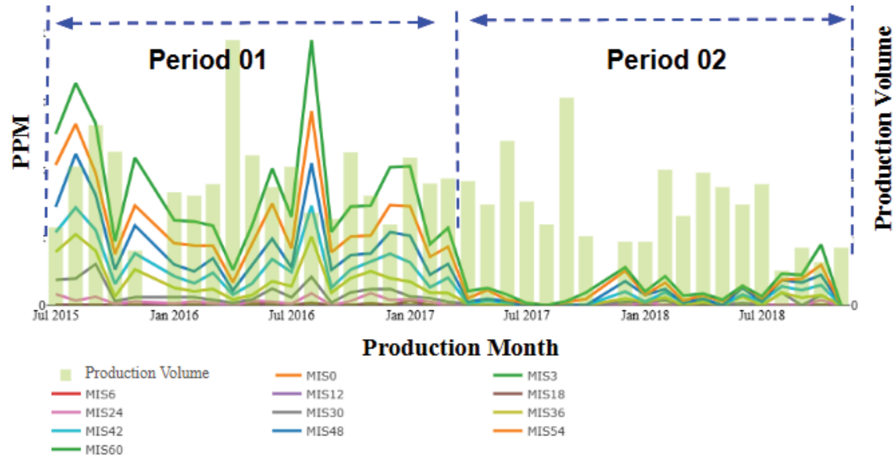

Fig. 5. Isochrone Chart for 5 Years Mature Data

enabling identification of distinct claim behavior patterns. Based on this analysis, the warranty data were segmented into two production periods: Period 01, characterized by a high-PPM spike, and Period 02, exhibiting comparatively lower PPM levels.

4.1. *Method Validation Using Mature Warranty Data*

Prior to applying the proposed methodology to the full dataset, the Tier-1 supplier sought to validate the approach against observed product behavior. Given that long-term failure characteristics can vary significantly across regions and applications, only five years of mature warranty data were initially used to forecast the sixth year of warranty returns. The forecasted results were then compared with actual field data to assess model validity.

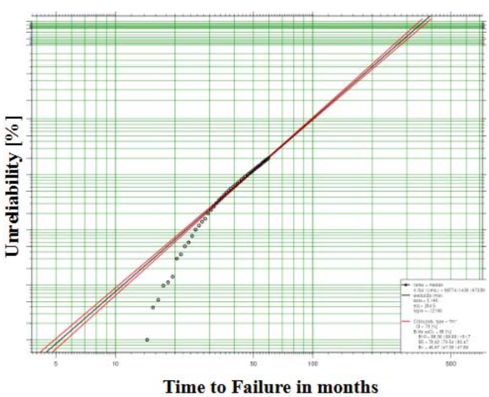

Fig. 6. Weibull graph for 5 Years Mature Data

The two production periods identified from the Isochrone chart were retained for this validation exercise, as shown in Figure 5. The resulting lifetime plots for the five-year data revealed concave or non-linear Weibull behavior (refer Figure 6), indicating that a simple single-distribution model may not adequately represent the underlying failure mechanisms.

4.1.1. *Non-linear Weibull behavior*

Non-linear Weibull behavior can arise due to several factors, including: (i) bathtub-shaped failure characteristics, (ii) mixed populations, (iii) varying environmental conditions, (iv) mixed-age components, (v) three-parameter Weibull behavior, (vi) non-standard lifetime distributions, (vii) multiple failure modes, and (viii) rollout or phased production effects. A detailed discussion of these factors is provided in the paper (James A. McLinn 2010). When such non-linear behavior is observed, careful selection of lifetime distribution models becomes critical. Guidelines for distribution selection under these conditions are summarized in Table 1, with further details provided in the paper (James A. McLinn 2010). After evaluating multiple candidate models, the three-parameter (3P) Weibull distribution was found to provide the best fit for Period 01, while the lognormal (Log) distribution best represented Period 02. The forecasted warranty returns based on these models fell within the 90% upper confidence limit of the actual sixth-year warranty data, as shown in Table 2, thereby validating the proposed methodology.

Table 1. Non-linear curve guideline

Possibility	**Analysis**
1) Two parameter Weibull or Normal	Not very likely for a curve on Weibull.
2) Two parameter Lognormal	Possible, look at cross-over, is it near 50%?
3) Three parameter Weibull	Possible, look at both the MLE and Rank Regression methods.
4) Three parameter Lognormal	Possible, try this for fit and corrected line.
5) Three parameter Normal	Possible, try this for fit and corrected line.
6) Mixture of 2 or more groups	Two groups seem most likely. Check failure modes for additional information.

Table 2. Forecast Result using 5 Years Mature Data (Difference between Estimated & Actual)

Warranty	Mean (Period 01+Period 02)					90% UCL (Period 01+Period 02)				
Year	2P+2P	Log+2P	3P+3P	Log+Log	3P+Log	3P+Log	Log+Log	3P+3P	Log+2P	2P+2P
0 to 4	-11.65%	-7.92%	-6.91%	-7.68%	-6.83%	-0.62%	-1.64%	-0.70%	-1.89%	-5.60%
0 to 5	-5.72%	-5.56%	-5.75%	-5.58%	-5.76%	-0.48%	-0.33%	-0.47%	-0.32%	-0.43%
0 to 6	4.14%	-2.78%	-2.71%	-3.44%	-3.06%	3.05%	2.45%	3.55%	3.35%	11.00%
0 to 7	24.53%	7.16%	8.64%	5.37%	7.66%	15.83%	12.81%	17.39%	15.48%	35.05%

4.2. *Application to Full Warranty Dataset and Long-Term Forecast*

Following validation, the proposed methodology was applied to the complete eight-year warranty dataset. Similar to the validation phase, non-linear Weibull behavior was again observed in the lifetime plots (refer Figure 7).

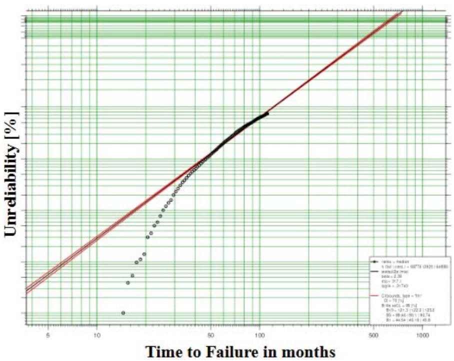

Fig. 7. Weibull graph for All Data

For Period 01, a mixed-Weibull model with two subpopulations (see Figure 8) provided the best representation of the failure behavior, while the lognormal distribution remained the most suitable model for Period 02 (see Figure 9).

All model fitting and evaluation were performed using Weibull++ software by ReliaSoft.

A comparison of actual versus forecasted warranty returns is shown in figure 10. Up to the sixth year, where warranty data were saturated, the actual claims consistently fell within the 90% upper confidence limit of the model estimates. Based on the selected lifetime models, the total number of warranty returns was forecasted to be near 10,000 units over the extended 15-year warranty period. This value includes the actual claims observed during the first eight years. The corresponding probability density function (PDF), shown in Figure 11, illustrates that the mixed-Weibull model for Period 01 and the lognormal model for Period 02 closely capture the observed product failure behavior across the warranty horizon.

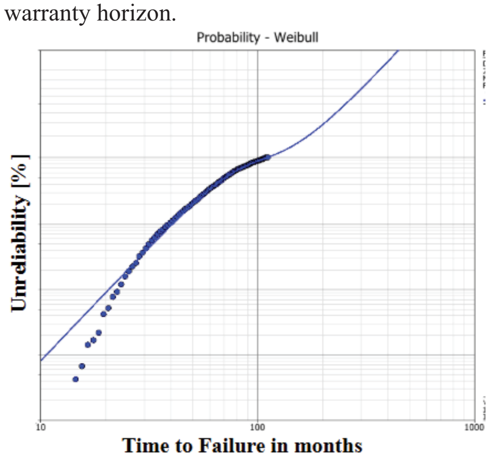

Fig. 8. Period 01 - 2 Subpopulations Mixed Weibull

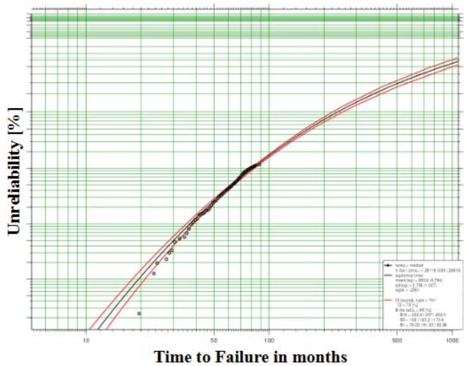

Fig. 9. Period 02 - Lognormal Distribution

4.3. *Adjustment for Vehicle Scrappage Rate*

In long-term automotive warranty forecasting, vehicle survivability must also be considered. After approximately ten years of service, a certain proportion of vehicles are no longer operational due to scrappage or deregistration, and therefore no longer contribute to warranty exposure. Vehicle survivability is highly region-dependent. Based on an analysis of the supplier's historical warranty data, it was estimated that approximately 20% of vehicles are removed from service between 10 and 15 years of operation.

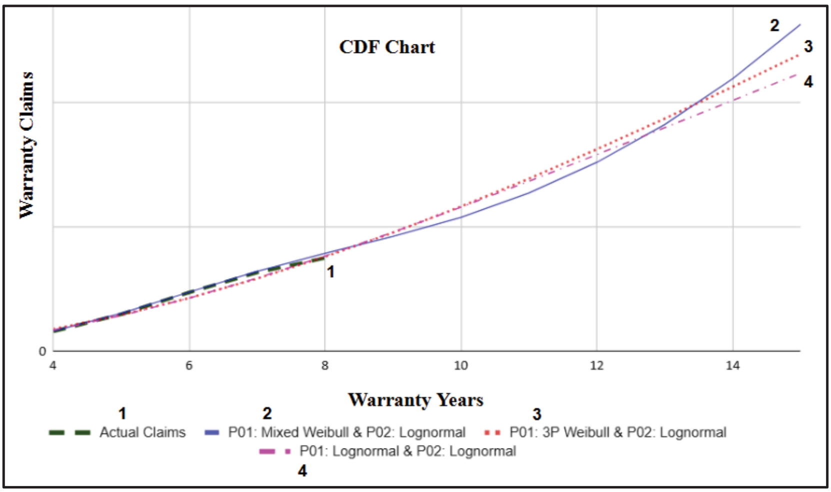

Fig. 10. Actual vs Forecasted results comparison

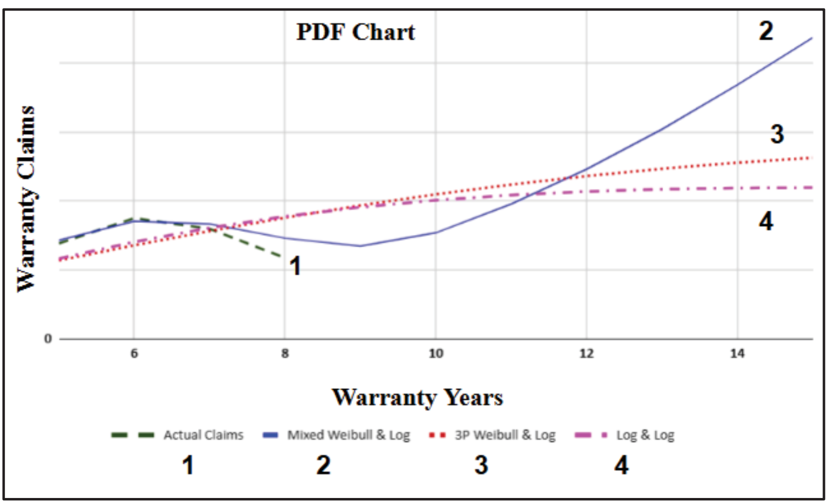

Fig. 11. PDF comparison graph for mixed life distributions

Accordingly, this scrappage factor was incorporated into the final forecast by reducing the estimated warranty returns by 20% beyond the tenth year. The adjusted forecasted warranty returns were then used to calculate the associated warranty cost for the extended warranty period.

5. Conclusion

Extended automotive warranty programs driven by regulatory and market requirements pose significant challenges for accurate warranty risk assessment, particularly for Tier-1 suppliers with limited visibility into vehicle sales and usage. This paper presented a structured statistical methodology that integrates industrial constraints with reliability modeling to improve long-term warranty return forecasting. The proposed approach combines systematic warranty data cleaning, exposure alignment using vehicle sales distribution and shipping-time adjustment, PPM-based segmentation through Isochrone charts, and appropriate lifetime distribution selection for heterogeneous failure populations. By explicitly addressing mixed quality populations, multiple failure modes, and right-censored warranty data, the methodology enables realistic modeling of field failure behavior under extended warranty conditions.

Application to an industrial automotive case study demonstrated strong agreement between forecasted and actual warranty returns, with observed claims remaining within the 90% upper confidence limits. Mixed-Weibull and lognormal distributions were successfully applied to distinct production periods, providing reliable estimates of warranty returns up to a 15-year horizon. Incorporation of vehicle survivability through a scrappage-rate adjustment further enhanced the realism of long-term forecasts.

Overall, the proposed framework offers a practical and robust solution for extended warranty risk assessment and supports improved warranty provisioning and risk management decisions in automotive applications.

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