Proc. of the European Safety and Reliability Conference (ESREL 2026)
Edited by José C. Matos, Paulo B. Lourenço, Michael Beer, Daniel Oliveira, Edoardo Patelli, Hélder S. Sousa, Rui A. Silva and Monica Santamaria

doi: 10.3850/ESREL2026061419_esrel26-p28957-cd

Censored Field Data: Impact and Consideration on Reliability Analytics in Product life cycle – A Case Study on Light Electric Vehicles

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The technical reliability of components in technical systems and products has a significant impact on the long-term reliability of products and thus on the sustainable use of energy and resources. Long-term reliability of components means that the product needs to be replaced later and that the components are potential candidates for carry-over parts (COP) regarding the next product generation, and can also be used after refurbishment as part of a second life phase (e.g. fair value repair). However, this requires a precise Model of the failure behaviour respectively the technical reliability of the component. The technical reliability of a component or product can be mapped using failure models based on field data (e.g. operating data, load collectives, damage data). In most cases, censored field data is a challenge and must be taken into account. Depending on the degree of censoring, failure models are subject to uncertainty regarding the expected failure rate or probability of failure. The study which is presented in this paper examines the impact of various failure models on the example of predictive product maintenance cycles based on censored field data. The aim is to compare commonly used prediction models and determine their effects on component reliability predictions. In a first step, various methods for modelling failure behaviour in the case of censored data (Kaplan-Meier estimator, Johnson method, Eckel candidate method) are compared. In a second step, the influence on an exemplary predictive maintenance scenario is determined. The study is conducted using a mechanical transmission component from a light electric vehicle (LEV), for which field data from an LEV fleet in the usage phase was recorded over two years of operation.

Keywords: Light Electric Vehicle Case Study, Censored Field Data, Weibull Distribution, Johnson Method, Kaplan-Meier Method, Eckel Method.

1. Introduction

The long-term reliability of components has a significant impact on the sustainability of a product. It directly influences the timespan of how long a product can be used without the need to repair, generates potential use cases as carry-over parts (COP) for subsequent product generations and improves the likelihood of components to be used in second-life applications.

Failure models are often generated in order to portray the failure rate of a component and to assess and predict its long-term reliability behaviour. Multiple models have been developed to extrapolate failure rate predictions from a limited set of known failure cases to a larger group of products in the field, such as Kaplan and Meier (1958), Johnson (1964) and Eckel (1977). When choosing a method for this model prediction, a central question concerns how to incorporate known data from in-field products into the model to obtain an accurate representation of the real failure behaviour of the relevant component, which can be used to assess the quality, reliability and resource efficiency of a component.

A longer lifespan of components impacts the classical failure behaviour as shown in Fig. 1. Shifting the so-called bathtub curve towards a lower random failure rate and later occurrence of wear out failure results in saved resources due to fewer necessary repairs and replacements of components. Simultaneously, accurate estimation of a component is required to precisely assess its failure behaviour.

Fig. 1. Failure rate and characteristic failure behaviour for mechanical and electric components (bathtub curve).

Bracke and Neupert (2020) compares various statistical models based on their accuracy to predict a simulated censored data set, while Severengiz et al. (2021) discusses how to implement reliability characteristics into the life cycle assessment of a product. This study investigates the impact of predictive models under varying but consistently applied model assumptions on reliability predictions and maintenance planning based on available field data. To compare these models and model assumptions, an exemplary predictive maintenance scenario is examined.

While resource efficiency is economically and ecologically advantageous, it is noted that technological advancements which reduce product emissions and running costs during its use phase are generally an important factor to consider, for example by providing the capability to upgrade relevant components to assure continued product efficiency. This work however is limited on mechanical components that are not necessarily the main focus of innovation. As such, the impact of these technological advancements will be disregarded.

2. Goal of Research Work

This paper focuses on the comparison of various prediction models of component failure rates based on the example of predictive maintenance scheduling. This is achieved by focussing on the following goals:

(i) Extrapolation of failure data using known models
(ii) Comparison of prediction models and the impact of common assumptions on fleet behaviour
(iii) Impact assessment of the component based on maintenance intervals under consideration of multiple prediction models

The case study is conducted on data collected for a mechanical transmission component of a light electric vehicle (LEV) over two years.

3. Methodology

Reliability models are used for failure behaviour prediction of a product or component, providing insight into its likely behaviour over its lifespan. Predictive models can be consulted during product testing as well as during product usage, e.g. to analyse whether the lifespan of a component matches its intended lifespan, to reuse a component or its design for a future product or to plan product maintenance and component replacements.

This study focuses on the reliability models proposed by Kaplan and Meier (1958), Johnson (1964) and Eckel (1977). The models serve as a decision basis for a product maintenance scenario based on expected failure rates of one product component.

3.1. *Reliability Model*

The Weibull distribution function, named after Weibull (1951), is an exponential distribution function defining the failure rate F in relation to a runtime variable t as

$$F(t) = 1 - e^{-\left(\frac{t-t_0}{T}\right)^b}, \qquad (1)$$

where the three parameters b, T and t_0 denote the shape parameter, the scale parameter and location parameter respectively. Note that the runtime variable t may refer to time spans, such as the time passed since production, but other measurements, such as kilometrage, can function as the runtime variable as well.

For this research, a two parameter Weibull model is considered, where $t_0 = 0$, thus

$$F(t) = 1 - e^{-\left(\frac{t}{T}\right)^b}. \qquad (2)$$

The empirical failure rate is estimated using the rank r_j of each corresponding failure, to be precise

$$F(t_j) = \frac{r_j - 0.3}{n + 0.4}, \qquad (3)$$

where n is the number of available data points. The parameters of the Weibull distribution function are subsequently estimated by means of the least-squares method.

3.1.1. *Johnson Method*

The rank correction method introduced in Johnson (1964) takes non-failed candidates into account in order to describe the failure rate of a component. The rank of each failure case is adjusted by

$$r_j = r_{j-1} + x_j \cdot \frac{1 + n - r_{j-1}}{1 + n_j}, \qquad (4)$$

where x_j and n_j denote the number of failed units and the number of candidates that are still under observation at time t_j

3.1.2. *Kaplan-Meier Method*

Kaplan and Meier (1958) propose a rank correction method based on the multiplication theorem of probability. The survival probability p_j at $t = t_j$ is estimated by the number of candidates still in observation and the number of failed candidates, to be precise

$$\hat{p}_i = \frac{n_i - x_i}{n_i}. \qquad (5)$$

The estimated failure rate is then obtained as

$$F(t_j) \approx \hat{F}(t_j) = 1 - \prod_{i=1}^{j-1} \hat{p}_i\,. \qquad (6)$$

3.1.3. *Estimation of potential candidates*

If limited information is known about the candidates, the number of potential candidates for a rank correction as proposed by Johnson (1964) and Kaplan and Meier (1958) can be estimated.

One common approach is to split all candidates into groups of size k, so that every group contains one known failure. When a candidate fails, all candidates within its group are treated as suspended from supervision, thus

$$n_j = n - (j - 1) \cdot k. \qquad (7)$$

This method is often referred to as the sudden death method (SD). It is commonly used in prototype testing to estimate the failure rate of a tested product or component based on a smaller sample size (Bracke 2022).

An alternate approach is to assume that no candidate is suspended before the last known failure, subsequently referred to as the non-suspended method (N). Predisposition of a perfect correlation between the time in field and the runtime variable t as well as a minimum runtime at least the runtime of the last known failure results in

$$n_j = n - j. \qquad (8)$$

It is noted that both assumptions presented in this section are expected to deliver less accurate failure rate predictions than using the actual runtime data. This however requires the data to be obtainable which can not always be ensured depending on the product and its application.

3.1.4. *Eckel Method*

Finally, a rank correction method developed by Eckel (1977) is considered where potential candidates are considered by their usage profile which can often be described by a lognormal distribution, to be precise

$$n_{\mathrm{an},j} = n \cdot F_{\mathrm{ln}}(t_j | \mu_{\mathrm{ln}}, \sigma_{\mathrm{ln}}) - X_j - \sum_{i=1}^{j-1} n_{\mathrm{an},i}\,, \qquad (9)$$

Where X_j, μ_{ln} and σ_{ln} denotethe cumulated number of failures att_j as well as the mean and standard deviation of the distribution respectively. The fictitious cumulative candidate frequency $F_{\mathrm{an},j}$ and corrected failure rate $F_{\mathrm{k},j}$ are then obtained iteratively as

$$F_{\mathrm{an},j} = F_{\mathrm{an},j-1} + \frac{n_{\mathrm{an},j}}{(n+1) \cdot (1 - F_{\mathrm{k},j})}, \qquad (10)$$

$$F_{\mathrm{k},j} = F_{\mathrm{k},j-1} + \frac{X_j}{(n+1) \cdot (1 - F_{\mathrm{an},j})}, \qquad (11)$$

where $F_{\mathrm{an},0} = F_{\mathrm{k},0} = 0$.

The Eckel candidate method is applied to a fleet at a specific point in time, e.g. when all candidates are in the field for one year. Subsequently, the relative difference of the observation time of the candidates has to be small in order to deliver accurate results.

3.2. *Impact Assessment*

The analysed models are compared in regards to their impact on the necessity of repair cycles that arises from component failures. The following assumptions are made for the purpose of this research:

- The LEV is intended to last for a set lifetime
- Components will be replaced upon failure
- Maintenances are conducted at regular intervals based on the expected failure rates

Applying this framework based on obtained prediction data provides a basis for comparison based on the number of repair cycles that are expected for each scenario. While this method does not account for more complex factors of the applied maintenance strategy, such as global warming potential or the handling of maintenance intervals for multiple components, it serves as a simplified approach to identify the sensitivity of planned repairs with respect to various rank correction methods. It is noted that the identification of a component as a candidate as a carry-over part or for a second life use, while theoretically transferable, is not considered further.

4. Case Study LEV

This chapter outlines the studied data set and summarises the considered predictive models. The models are briefly compared and evaluated based on their potential accuracy as well as their impact on a simplified component maintenance scenario.

4.1. *General Approach and Data Set*

The study is conducted on a data set acquired from a fleet of 1425 LEV of the same model. The vehicles are built within the same year and under observation for up to 18 months. For the purpose of this study, a mechanical transmission component is considered. The failure behaviour is filtered so that one error pattern is isolated.

The data required for each LEV includes date of production and distance travelled either at the end of the observation phase or at the time of failure. In cases where the travel distance is unknown at failure, but known at the end of observation, the kilometrage is estimated from the given data. These cases arise when the LEV is repaired, though they are treated as failures and removed from observation within this analysis. Incomplete data entries are subsequently disregarded for the sake of direct model comparibility, leaving a final data set consisting of 621 LEV including 51 candidate failures.

4.2. *Reliability Analysis*

The pattern of use of the analysed LEV is presented in Fig. 2 with an average kilometrage of 1243.813 km and an average performance of 109.905 km/mo. The usage profile is approximated by a lognormal distribution using the maximum likelihood estimator with $\mu = 75.863$ and $\sigma = 1.009$. The Spearman correlation coefficient between the kilometrage and time under observation is estimated to be $0.147 \leq \hat{r} = 0.223 \leq 0.296$ at a confidence interval of $\gamma = 0.95$, indicating a very weak positive correlation between these parameters.

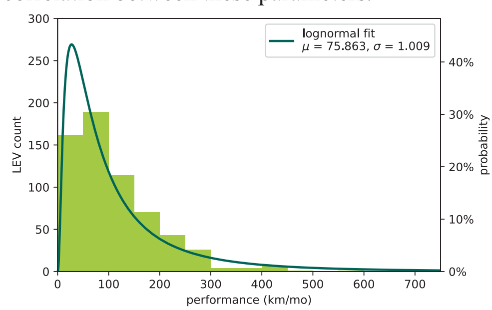

Fig. 2. Distribution of monthly kilometrages for the LEV fleet and fitted lognormal distribution based on the estimated performance after one year.

Two-parameter Weibull models are used to approximate the failure models. The model parameters obtained for the failed candidates are listed in Table 1.

Table 1. Results of the two-parameter Weibull fit for the known failures of the analysed data set. The lower and upper limits $\bullet_\text{l}$ and $\bullet_\text{u}$ are estimated for a confidence level of $\gamma = 0.95$.

Param.	Unit	Weibull-fit (Failures)
b	-	1.494
b_l	-	0.747
b_u	-	2.989
T	km	1035
T_l	km	661.4
T_u	km	5266

Subsequently, the indices $\bullet_\text{F}$, $\bullet_\text{J}$, $\bullet_\text{KM}$ and $\bullet_\text{E}$ refer to the failures as well as the Johnson, Kaplan-Meier and Eckel methods respectively.

4.2.1. *Johnson Method*

The failure rate of the fleet as predicted by the Johnson method is extrapolated by identifying the number of candidates which fall out of observation based on their known kilometrage and again using the sudden death assumption (cf. Table 2).

Table 2. Weibull parameters for the Johnson rank correction method ($\gamma = 0.95$).

Param.	Unit	Johnson		
		Data	SD	N
b	-	1.355	1.500	1.109
b_l	-	0.678	0.750	0.554
b_u	-	2.710	2.999	2.217
T	km	7300	5450	15991
T_l	km	4453	3487	8740
T_u	km	43900	27566	143292

The resulting Failure rate models are shown in Fig. 3. The sudden death assumption leads to a parallel shift of the Weibull distribution function on double logarithmic paper with $b_{\text{J, SD}} \approx b_\text{F}$. As such, the sudden death method can be interpreted as a neutral leaning assumption regarding failure behaviour.

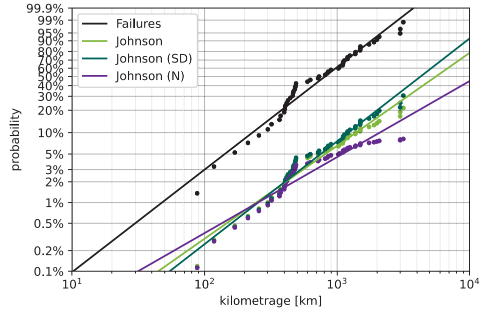

Fig. 3. Weibull distributions obtained from the Johnson method using kilometrage data of the analysed data set, the sudden death method and without suspensions respectively.

When accounting for the time of observation as derived from the data set, a shift in the Johnson shape parameter b_J is observable as a majority of candidates may be under observation for a longer period than the majority of known failures, thus lowering the expected failure probability for higher runtimes compared to the sudden death approach. This effect is most pronounced when the assumption of no suspensions is made, further flattening the predicted curve. The non-suspended candidates approach consequently biases towards an early failure behaviour interpretation.

4.2.2. *Kaplan-Meier Method*

The model prediction based on Kaplan and Meier (1958) is once again conducted based on known kilometrage data and on the sudden death method respectively. The estimated Weibull parameters are listed in Table 3.

Table 3. Weibull parameters for the Kaplan-Meier method ($\gamma = 0.95$).

Param.	Unit	Kaplan-Meier		
		Data	SD	N
b	-	1.312	1.456	1.063
b_l	-	0.656	0.728	0.531
b_u	-	2.624	2.913	2.125
T	km	7716	5680	17795
T_l	km	4632	3586	9475
T_u	km	49198	30149	175285

The shape parameters b_KM and $b_{\text{KM, SD}}$ are 3 %to 4.2 % lower than when using the Johnson method while the scale parameters increase by 5.7 %, 4.2 % and 11.3 % respectively (cf. Fig. 4).

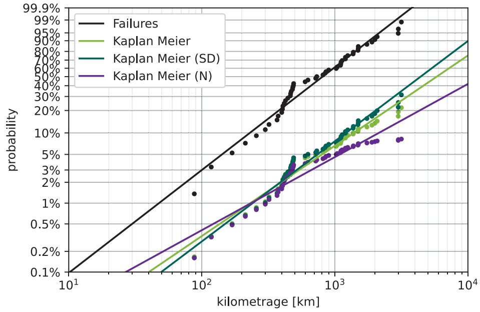

Fig. 4. Weibull distributions estimated by the Kaplan-Meier rank correction method. The candidates are obtained from kilometrage data and by applying the sudden death method and non-suspension method.

4.2.3. *Eckel Method*

For the Eckel method, a field usage time of twelve months is assumed for every candidate. The curve flattens (cf. Fig. 5), leading to the assumption that a majority of candidates are presumed to survive past the majority of failures.

Table 4. Weibull parameters for the Eckel candidate method ($\gamma = 0.95$).

Param.	Unit	Eckel
b	-	1.063
b_l	-	0.531
b_u	-	2.126
T	km	17831
T_l	km	9496
T_u	km	175539

The obtained Weibull parameters are similar to the non-suspended Kaplan-Meier method with $b_{\mathrm{KM,\,N}} = b_{\mathrm{E}}$ and $T_{\mathrm{KM,\,N}} \approx T_{\mathrm{E}}$ (cf. Table 4), leading to the assumption of a random failure behaviour. The curve flattens in comparison to the failure Weibull model, leading to a sharp downwards correction of predicted failure rates for higher kilometrages (cf. Fig. 5).

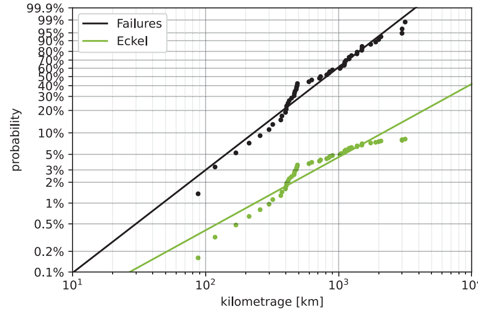

Fig. 5. Results of the Eckel candidate method. Candidate usage profile is approached by a lognormal distribution assuming a field use time of 12 months.

4.3. *Impact Assessment*

A simplified examplatory maintenance scenario is examined in order to assess the potential impact of the deviations between the model predictions for the presented methods. For this scenario, the LEVs are assumed to have a predicted lifespan of 9000 km. The analysed component is replaced during each maintenance regardless of its currently assumed degradation state. Maintenance is performed on the LEVs in intervals of B_5, B_{10} and B_{20} respectively during its life cycle. The number of required maintenances proposed for this approach are presented in Fig. 6.

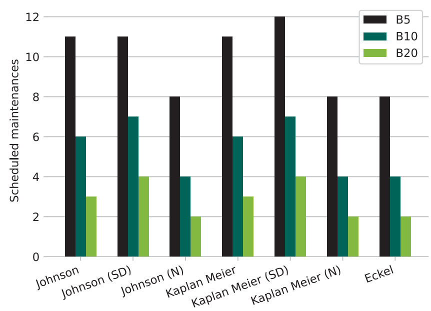

Fig. 6. Number of predictive maintenances required for the analysed component of the LEV based on a lifetime expectancy of 9000 km.

The number of maintenance intervals ranges from 2 to 12 depending on the chosen predictive model and censored data treatment. The Kaplan Meier method and Johnson method each predict 6 required maintenances for the analysed component when choosing B_{10} as the replacement limit. Both methods deliver similar results due to the similarity of their Weibull parameters, only deviating from one another at increased planned maintenance counts (B_{20}) at 11 maintenances for the Johnson method and 12 maintenances for the Kaplan Meier method.

Applying the sudden death assumption to both models for the same data set increases the planned maintenance count to 7 at B_{10}. The Eckel method matches the lowest number of predicted maintenances, matching the predictions of the non-suspension assumption at 4 maintenances during the assumed lifespan of each LEV.

5. Discussion

While some of the presented prediction methods deliver similar results, such as the Kaplan-Meier method and Johnson method under identical assumptions regarding candidate treatment, the approximation of censored field data heavily impacts the prediction of failure behaviour of the analysed mechanical component and subsequently planned maintenance scheduling. The field runtime data provides a more accurate estimate of the performance of the component in field use. The sudden death approach as well as non-suspended candidate treatment intend to approximate the expected component performance. This can prove to be instrumental when dealing with incomplete or insufficient data, which may especially occur if a component is not field tested, e.g. during product testing, or if the field data is generally not collected. Both assumptions may deliver accurate results if the real product usage is similar to the model assumption. Assuming unsuitable failure patterns will however lead to increased or reduced maintenances, which in return generates the risk of increasing costs due to redundant repairs or unplanned maintenance.

The Eckel method differs from Kaplan-Meier and Johnson as it estimates the candidates by means of a lognormal distribution. The required data may be acquired from similar usage profiles of previous product models or incomplete usage data. The method is applied to the data set under the assumption that all candidates have a field time of 12 months. Since the actual field times range from 6 to 18 months, the accuracy of the Eckel method is limited. Furthermore, the field time and the lifespan variable show a very weak correlation, implying that the estimation of kilometrage based on months in service is not necessarily applicable.

The assessment of the estimated maintenance cycles shows that planned maintenance patterns may change drastically depending on estimated fleet behaviour and subsequent model assumptions. While treatment of unknown field data based on common assumptions are likely to deliver less accurate predictive models, they can be beneficial if the provided data is insufficient, potentially leading to an over- or underestimation of required maintenances. Carefully considering the applicability of each assumption to the regarded component consequentially proves to be vital. True field data is however expected to deliver more accurate failure behaviour predictions and should be preferred. It is furthermore beneficial to re-assess potential maintenance schedules based on collected field data as it is produced.

6. Summary and Conclusion

This study compared common approaches to the failure rate prediction of product components based on collected data for a mechanical component of a light electric vehicle. The component failure rate was estimated under various assumptions made on the fleet behaviour. The predictions were utilised to generate replacement strategies in order to assess the impact of the discussed models on predictive maintenance.

The study has shown that the treatment of potential failure candidates significantly impacts the failure rate of a component and subsequently maintenance planning, whereas the choice of the failure rate model is of comparatively low impact when comparing specifically the Johnson method and the Kaplan Meier method. While assumptions on fleet behaviour can substitute for missing data given that the underlying assumption is applicable to the usage scenario, complete and accurate usage data is expected to deliver the most accurate prediction.

Additional research can be done to include other failure rate prediction models, such as the RAPP method (Bracke 2013). Furthermore, a life cycle assessment can function as a more detailed assessment of the ecological and economical impact of model inaccuracies.

Acknowledgement

Research funding was provided by the Deutsche Bundesstiftung Umwelt (DBU) as part of the research project *End-of-Life-Strategien für Light Electric*

Vehicles innerhalb einer digitalisierten Kreislaufwirtschaft am Beispiel von E-Lastenrädern – KREISRAD (Award No. 39868/01).

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