Proceedings of the 33rd European Safety and Reliability Conference (ESREL 2023)
Edited by Mário P. Brito, Terje Aven, Piero Baraldi, Marko Čepin and Enrico Zio

doi: 10.3850/978-981-18-8071-1_P307-cd

Identification of risky parts in a product fleet in the usage phase based on cluster analysis – case study light electric vehicle in the urban environment

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The increasing complexity of product functionality and manufacturing processes often leads to complex failure modes and reliability problems within the product usage phase. This paper outlines an approach to determine and identify risky parts in product fleets based on cluster analysis with respect to product failure behavior and usage load profile. The theory and application of the approach are shown with the help of a data base of a light electric vehicle (LEV) product fleet in the usage phase. Three cluster algorithms are applied in the case study: hierarchical clustering with a Euclidean distance measurement and Ward Linkage, hierarchical clustering with a City-Block distance measurement and Ward Linkage, and partitioned clustering with k-means algorithm. The impact of the use of these different distance determination methods respectively fusion algorithms is analyzed. In addition, a comparison with state-of-the-art risk analyses using Weibull distribution models with candidate prognosis (sudden death) for the whole population and the subpopulation of the risky parts in the product fleet is conducted. As a result, recommendations for field measures (recall and maintenance actions with regard to prioritization and partial maintenance) are derived and evaluated based on the data analyses.

Keywords: risk analysis, product fleet, load profile, cluster analysis, Weibull, recall, maintenance, light electric vehicle.

1. Introduction

The increasing complexity of product functionality and manufacturing processes often leads to complex failure modes and reliability problems within the product usage phase. The mass production of consumer goods results in product fleets – like light electric vehicles (LEV) – with comparable construction revision level. A failure mode leads to a spreading failure behavior with regard to the product fleet and to an increasing percentage of customer complaints. The percentage of failures respectively complaints with regard to the product fleet (population) in the usage phase depends on the failure mode as well as the usage load profile. The goal of the original equipment manufacturer (OEM) is the early detection of the risky parts of the product fleet for the initiation of measures like recall actions (reactive) or maintenance planning (active). State of the art is the use of Weibull distribution models (Weibull 1951) in combination with candidate prognosis. The Weibull distribution model describes the failure behavior, the candidate prognosis (e.g. Kaplan-Meier estimator (Kaplan Meier 1958) or Eckel-candidate method (Eckel 1977)) considers the non-failed units (because of the censored data). The precondition of these methods is the assumption, that every non-failed unit of the product fleet is a potential candidate (potential damage case). But this assumption is not fulfilled in every damage case, rather the number of potential candidates is depending on failure mode and usage load profile. The use of cluster analysis allows the determination of risky parts in product fleets in the usage phase, based on product operating data, like driving distance, operating hours, cf. Bracke et al. (2016).

This paper outlines an approach to determine and identify risky parts in product fleets based on cluster analysis with respect to product failure behavior and usage load profile. The theory and application of the approach is shown with the help of a data base of a light electric vehicle (LEV) product fleet in the usage phase.

2. Goals of research work and case study

The overarching goal is the risk analysis regarding a product fleet in the usage phase in the face of an upcoming failure focus; cf. sec. 2.1. The approach of the risk analysis is shown within a case study dealing with a light electric vehicle (LEV) product fleet; cf. sec. 2.2.

2.1. *Overarching goals*

The goals of the research study are as follows:

1. Identification of risky parts (subpopulations; failure candidates) via cluster analysis within the product fleet (population) in the use phase.
2. Analyzing the impact of the use of different distance determination methods respectively fusion algorithms within the cluster analyses.
3. Derivation of recommendations for reactive (recall; e.g. prioritization) and preventive (maintenance) field measures.

2.2. *Case Study: Framework*

Table 1. Case study light electric vehicle (LEV) fleet in the usage phase; data set

Characteristic	Value
LEV (N)	245
Driver	1,731
Ride	9,269
Damages	22
Life span variable	Unit
Usage time	[-]
Driven distance	[-]
Locations	x,y
Damage data	
Damage cases (n)	22
Component L	Function critical
Failure mode	Wearout mechanism

Note: The LEV fleet data is an excerpt of a comprehensive fleet data set. The damage data is a synthetic data set and contains a realistic failure mode.

The approach for the product fleet risk analysis is applied on a data base regarding a light electric vehicle (LEV) fleet. Table 1 shows the characteristics and the data arrays of the LEV fleet data base.

3. Fundamentals

This section gives an overview regarding the statistical models, parameter estimators and cluster algorithms used in this paper.

3.1. *Cluster analysis*

Cluster analysis offers a way to classify univariate, bivariate and multivariate objects into groups (cluster) with certain similarity characteristics, cf. Backhaus et al. (2021). In general, cluster procedures can be distinguished in partitioned and hierarchical cluster procedures.

3.1.1. *Hierarchical cluster procedures*

Hierarchical cluster procedures can be distinguished in agglomerative (bottom-up) and divisive (top-down) procedures.

The process of a hierarchical cluster analysis can be divided into the following three steps:

1. Determination of (geometrical) distances,
2. Choice of the fusion algorithm,
3. Calculation the number of clusters.

In the first step the choice of distance measure is necessary to estimate the next neighbors. The most commonly used distance measurements are the Euclidian (cf. Eq. (1)) and the City-Block measurement (also called Manhattan metric or taxicab metric; cf. Eq. (2)), both used in this paper.

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \quad (1)$$

$$d = |x_2 - x_1| + |y_2 - y_1| \quad (2)$$

As a fusion algorithm the Ward Linkage (WL) method is used in this paper. Here, the clusters are merged that lead to the smallest increase in the variance of the new cluster. The diversity is determined according to Eq. (3). Ward (1963).

$$D_{WL}(C_i, C_{i'}) = \frac{n_i n_{i'}}{n_i + n_{i'}} \|\overline{x_i} - \overline{x_{i'}}\|^2 \quad (3)$$

3.1.2. ***Partitioned cluster procedures: k-means***

The goal of the iterative k-means algorithm is the dividing of multidimensional data points x_i into k clusters c_k, so that the quadratic deviation between the empirical mean respectively the cluster center μ_{ck} of the particular cluster c_k with the associated data points $x_i \in c_k$ is minimal; cf. Eq. (4).

$$J(c_k) = \sum_{x_i \in c_k} \left\| x_i - \mu_{c_k} \right\|^2 \qquad (4)$$

The algorithm pursues the goal of minimizing the quadratic error over all clusters $\boldsymbol{C} = \{c_1, \ldots, c_n\}$; cf. Eq. (5). Since the squared error decreases with increasing number n_c of clusters, this must be fixed during the optimization. The proximity to the cluster centers is calculated by the Euclidean distance.

$$J(\boldsymbol{C}) = \sum_{k=1}^{n_c} \sum_{x_i \in c_k} \left\| x_i - \mu_{c_k} \right\|^2 \qquad (5)$$

3.1.3. ***Elbow-criterium***

The decision regarding the proper number of clusters is an essential part of the cluster analysis. For this purpose, the elbow criterion (Thorndike 1953) is used in this work. According to the elbow criterion, for ascending cluster numbers n_c the sum of the squared deviations within the clusters is determined according to Eq. (6); where x_j denotes an observation, c_k denotes the particular cluster and μ_{ck} denotes the associated cluster center.

$$W_c = \sum_{k=1}^{n_c} \sum_{x_j \in c_k} \left\| x_j - \mu_{c_k} \right\|^2 \qquad (6)$$

If W_c is plotted for ascending cluster numbers n_c, the knee point indicates the appropriate cluster number.

3.2. ***Weibull Model and Sudden Death***

The use of a three-parameter Weibull distribution model is common in reliability analytics: The model is flexible and from a mathematical point of view easy to handle (Bracke 2022). The three-parameter Weibull distribution model is given based on Eq. (7).

$$F(x) = 1 - \exp\left(-\left(\frac{x - t_0}{T - t_0} \right) \right)^b \qquad (7)$$

Besides the life span variable t, the three parameters are threshold parameter t_0 (theoretical time to first failure), scale parameter T (characteristic life span) and the shape parameter b. With the help of the Weibull Model, essential phases of the failure behavior of a system can be mapped: Early failure behavior, random failure behavior (constant failure rate) as well as failure behavior due to runtime. The estimation of the parameters can be done with the help of various methods, e.g. Maximum-Likelihood-Estimator, Least squares or method of moments. In this paper, the Maximum-Likelihood-Estimator (MLE) by Fisher (1912) is used.

The Weibull distribution model is fitted to the damage data. Within the case study risk analytics LEV fleet, the damage data analysis is carried out to a specific point of time; therefore some LEVs are failed, the others within the fleet are potential damage candidates. As a consequence, the data are right censored and a correction is needed regarding data (considering both damage data and candidates). Here, the simple correction regarding Johnson (1964) is used. The method according to the „Johnson ranking approach“ takes into account the non-defaulted units (potential candidates) by assigning mean, hypothetical rank numbers in relation to the failed units. For further analytics, corrections, which are considering the usage profile, according to Kaplan Meier (1958) or Eckel (1977) are recommended.

3.3. ***Field measures***

This section deals with fundamentals of field measures with regard to failure prevention (active) and failure fixing (reactive) strategies with respect to product fleets in the usage phase.

3.3.1. ***Maintenance strategies***

In principle, a differentiation is made between three different maintenance strategies (cf. Bracke (2022)): Damage-dependent maintenance (“fire-fighting strategy”), time-based maintenance and condition-based maintenance. In the case of damage-based maintenance, the system failure is taken as the reason for performing the maintenance. In contrast, in time-based maintenance, maintenance work is performed at defined intervals, usually with reference to a life span variable interval (e.g. operating time). In condition-based maintenance, operating parameters and operating conditions are monitored (continuously by means of production data acquisition or by means of regular inspections) and maintenance work is scheduled and performed depending on the system condition. Condition monitoring systems are often used for condition-based maintenance.

3.3.2. *Recall actions*

In principle, the manufacturer of a product has the following superior options for reacting to a case of damage in his product fleet in the field:

a) Recall: The manufacturer recalls parts of its product fleet from the field that may be affected by a possible failure. The recall is usually carried out in the case of faults that result in safety-critical risks or a significant functional impairment.
b) Maintenance: Depending on the occurrence of the fault, preventive maintenance can also be carried out during regular inspection intervals. The precondition is that the products have not yet reached the critical operating time with regard to the failure. This type of failure handling is usually chosen for faults that result in impaired comfort or less severe fault symptoms.

Other options, such as targeting users (but without an official recall), are also possible.

4. Approach: Risk analysis of product fleets

This section outlines a procedure for field data analysis against the background of an upcoming failure focus within a LEV fleet in the field use phase. The aim is to detect critical subpopulations within the fleet as a starting point for fault rectification (reactive; recall) and/or fault prevention (preventive; maintenance) in the field.

1. Analysis of operating and failure data of a product fleet in the usage phase. The result is a set of life span variables (e.g.: operating time, charging cycles, distance).
2. Determination of life span variables with regard to the failure mode based on damage data (e.g.: damage point of time, damage characteristics).
3. Failure behavior based on damage cases and risk prognosis based on the whole population.
4. Cluster analyses for identification of risky parts (subpopulation) of the product fleet (population) and estimation of potential high-risk candidates.
5. Failure behavior and risk prognosis based on subpopulation (clusters).
6. Statistical analysis regarding the efficiency of field measures: assessment of maintenance strategies and recall actions.

5. Case study: Risk analysis of LEV fleet

In this section, the presented approach (cf. sec. 4) is applied to the case study data base of the LEV fleet (cf. sec. 2.2). At first, a risk analysis is conducted for the whole population (sec. 5.1). Secondly, the risky parts in the product fleet are identified using three different cluster algorithms (sec. 5.2). The risk analysis is repeated for the determined risky part in the population (sec. 5.3). Lastly, field measures are derived (sec. 5.4) and evaluated regarding their efficiency (sec. 5.5).

5.1. *Risk analysis regarding whole population*

This section shows the determination of the failure behavior of component L based on known damage data and with respect to the LEV fleet in the usage phase.

Fig. 1 shows the failure behavior of component L ($n = 22$ claims; cumulative failure probabilities; double logarithmic representation) with the help of a Weibull distribution model fit (parameter estimation: MLE; $t_0 = 173$; $b = 2.47$; $T = 239$; related to known damage cases; Fig.: 1: black line). Furthermore, the failure behavior is shown in relation to the entire fleet ($N = 245$): The failure probabilities were corrected using the Johnson approach and a Weibull model was fitted (parameter estimation: MLE; $t_0 = 173$; $b = 2.47$; $T = 353$; related to whole fleet; Fig.: 1: grey line). The failure mechanism wear is shown to be a typical, runtime-related failure behavior, which is reflected in the parameters of the Weibull distribution.

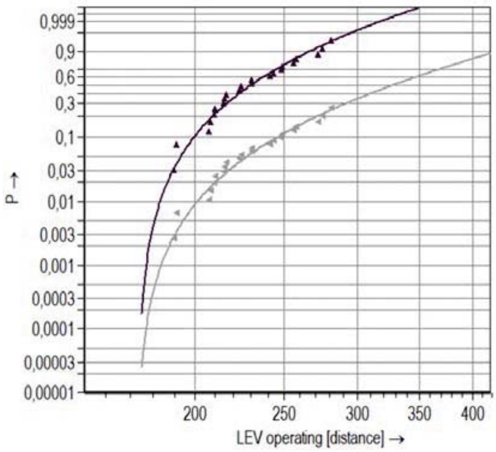

Fig. 1. Failure behavior component L; Weibull model fit based on known damage cases (black line); failure behavior fleet (grey line); Weibull model fit based on Johnson correction.

5.2. *Cluster analysis*

Three different cluster algorithms are applied to the LEV fleet data set considering the variables driven distance and usage time: hierarchical clustering with Euclidean distance measurement and Ward Linkage, hierarchical clustering with City-Block measurement and Ward Linkage, cf. sec. 3.1.1, and partitioned clustering with k-means algorithm, cf. sec. 3.1.2. For each cluster algorithm, the optimal number of clusters is determined using the Elbow-criterium, cf. sec. 3.1.3. In Fig. 2, exemplarily the elbow plot of the hierarchical clustering with Euclidean distance measurement and Ward Linkage is shown.

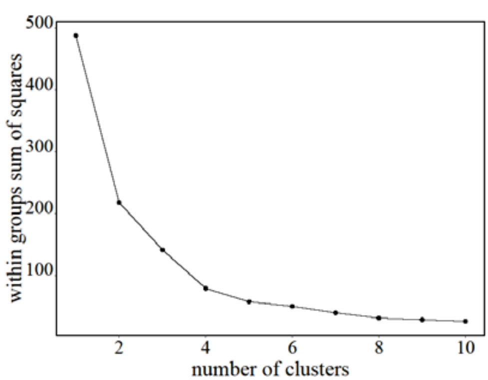

Fig. 2. Elbow plot of hierarchical clustering with Euclidean distance measurement and Ward Linkage.

The knee point is determined at three or four clusters. Considering the data situation and the behavior of the LEV fleet, the optimal number of clusters is set to four. The Elbow plot of the other two cluster algorithms is similar, so the analyses are conducted with four clusters for each algorithm. In Fig. 3 to 5, the clustering results are plotted.

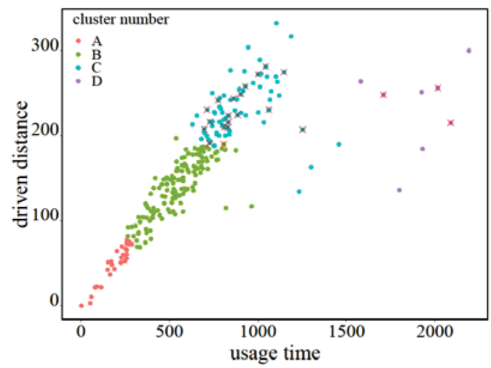

Fig. 3. Results of hierarchical clustering with Euclidean distance measurement and Ward Linkage; damage cases as red crosses.

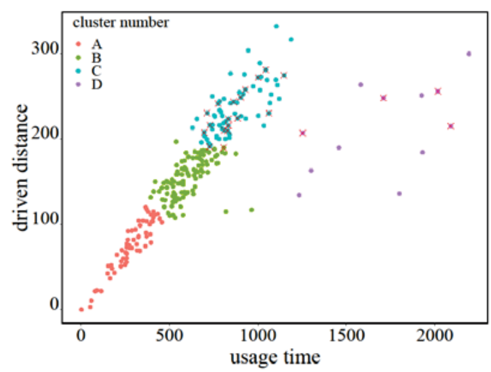

Fig. 4. Results of hierarchical clustering with City-Block distance measurement and Ward Linkage; damage cases as red crosses.

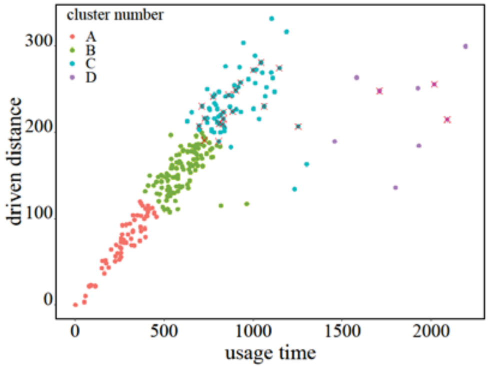

Fig. 5. Results of partitioned clustering with k-means algorithm; damage cases as red crosses.

With all algorithms, four groups with similar characteristics are clustered:

- Cluster A with short driven distance and short usage time,
- Cluster B with medium driven distance and short to medium usage time,
- Cluster C with long driven distance and medium usage time,
- Cluster D with medium to long driven distance and long usage time.

The damage cases are predominantly classified in cluster C for all methods; in addition, there are some damage cases in cluster D and a few in cluster B.

Using the hierarchical clustering with Euclidean distance measurement and Ward Linkage the number of values in Cluster A is lower than in the other algorithms, the maxima of driven distance and usage time are lower in this case. Apart from that, the applied algorithms are mostly consistent concerning their clustering, the accordance is in all cases above 80 %. Comparing the hierarchical clustering with City-Block distance and Ward linkage to the k-means clustering the accordance amounts to nearly 96 %.

5.3. *Failure behavior and risk analysis regarding clusters subpopulation*

This section shows the determination of the failure behavior of component L based on known damage data and with respect to the cluster C (hierarchical clustering with Euclidean distance measurement and Ward Linkage; subpopulation).

Fig. 6 shows the failure behavior of component L within cluster C (n = 18 claims; cumulative failure probabilities; double logarithmic representation) with the help of a Weibull distribution model fit (parameter estimation: MLE; t_0 = 177; b = 2.32; T = 240; related to known damage cases; Fig.: 6: black line). Furthermore, the failure behavior is shown in relation to the entire cluster C fleet (N = 74): The failure probabilities were corrected using the Johnson approach and a Weibull model was fitted (parameter estimation: MLE; t_0 = 177; b = 2.32; T = 301; related to whole fleet; Fig.: 6: grey line)).

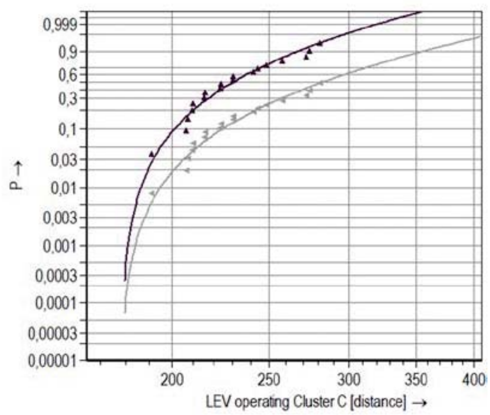

Fig. 6. Failure behavior component L within cluster C; Weibull model fit based on known damage cases in cluster C (black line); failure behavior cluster C fleet (grey line); Weibull model fit based on Johnson correction.

The failure mechanism wear is shown to be a typical, runtime-related failure behavior, which is reflected in the parameters of the Weibull distribution.

5.4. *Field measures*

Two field measures can be derived from the results of the cluster analyses: Firstly, the recall action in the current damage case and, secondly, recommendations for future maintenance planning.

The recall action can be prioritized by the absolute amount (strategy A) or the percentage of damage cases (strategy B) in the different clusters. For strategy A, the number of damage cases in each cluster is determined. Then, the LEVs in the cluster with the most damage cases are prioritized recalled. In the presented use case, these are the LEVs in cluster C – regardless of the cluster algorithm used, with negligible differences in the number of prioritized recalled LEVs. Secondly prioritized, the LEVs in cluster D would be recalled. The advantage of this strategy is the high coverage of damage cases due to the consideration of the absolute damage focus. In strategy B, the amount of damage cases is related to the total number of LEVs in the cluster. The LEVs in the cluster with the percentual highest amount of damage cases are prioritized recalled. In the presented use case, these are the LEVs in cluster D – regardless of the cluster algorithm used, only with negligible differences in the percentage. Secondly prioritized, the LEVs in cluster C would be recalled. The advantage of strategy B is the low number of LEVs to recall in the first recall action. The disadvantage is the low coverage of damage cases in the prioritized recall action. The quantification of these effects is shown in Table 2 in the next section. Note: If there is a safety-critical failure or a serious functional-critical failure (e.g. vehicle down), all vehicles must of course be recalled. In this case, the cluster analysis gives indications with regard to the sequence.

For future LEV production batches, three maintenance strategies can be derived from the results of the cluster analysis. Firstly, a threshold for the driven distance can be defined (strategy 1). For every LEVs with a higher driven distance, maintenance actions are recommended. Strategy 2 contains a threshold for the number of rides of a LEV derived from past damage cases. For every LEV with a number of rides above the threshold, maintenance actions are recommended. Lastly, maintenance actions are recommended for frequently driven LEVs in the fleet, defined by two thresholds based on the median of the driven distance and the median of the usage time (strategy 3). The efficiency of these maintenance strategies, assuming the same damage behavior in a future fleet with the same number of LEVs and the same load profile, is shown in Table 3 in the next section.

5.5. *Summary: Efficiency of field measures: maintenance assessment*

Table 2. Efficiency of recommended recall strategies with comparison of cluster algorithms.

strategy	cluster algorithm	prioritized recalled LEVs	percentage of detected damage cases
A	euclidean	74	81.82 %
	City-Block	69	72.73 %
	k-means	69	81.82 %
B	euclidean	8	13.64 %
	City-Block	12	18.18 %
	k-means	9	13.64 %

strategy A: Prioritized recall LEVs in cluster with absolute most damage cases.

strategy B: Prioritized recall LEVs in cluster with percentual most damage cases; Note: Safety-critical failures or serious functional-critical failures lead to a recall of all vehicles; cluster analysis gives indications regarding the sequence.

Table 3. Efficiency of recommended maintenance strategies with comparison of cluster algorithms.

strategy	maintained LEVs	percentage of detected damage cases
1	95	100 %
2	164	100 %
3	109	100 %

strategy 1: threshold for driven distance

strategy 2: threshold for number off rides

strategy 3: thresholds based on median of driven distance and usage time

6. Summary and Outlook

In this paper an approach to determine and identify risky parts in product fleets based on cluster analysis with respect to product failure behavior and usage load profile was presented, using the example of light electric vehicles (LEV) in the usage phase. The three applied cluster algorithms (hierarchical clustering with Ward Linkage and Euclidean or City-Block distance measurement, partitioned clustering with k-means algorithm) hardly differed regarding their group classification. For all algorithms, the optimal number of clusters was determined as four; comparing the algorithms the clustering agrees over 80% to 96%. In future analytics it is planned to compare the results of the applied cluster algorithms using performance metrics, e.g. Silhouette Score.

From the results of the cluster analyses, field measures (recall and maintenance actions) were derived. For a prioritization (sequence) within the recall action, a cluster wise approach is recommended. Comparing the number of recalled LEVs and the percentage of detected damage cases, it was outlined, that an appropriate approach is focusing the recall action on LEVs in the cluster containing the absolute most damage cases. The k-means algorithm is highlighted as the best cluster algorithm in this recall strategy. In contrast, the prioritization (sequence) within recall action with the percentual most damage cases is no appropriate approach due to the low coverage of damage cases in the product fleet in the prioritized recall action.

In comparison to state-of-the-art methods (Weibull distribution model with candidate prognosis) using cluster analysis for the identification of high-risk products, the prioritization (sequence) of field measures can be outlined. In case product comfort complaints (failures like noises), the field measure can be focused on certain clusters.

In addition, suggestions for the maintenance planning of future LEV fleets were derived from the data analytics. Thresholds for the damage-related parameters were defined. Assuming the same load profile as in the case study, the use of a threshold of the driven distance or the medians of the driven distance and usage time is recommended to minimize the number of LEVs to be maintained while providing a 100 % detection of risky products.

Comparing the failure behavior of component L based on all known damage events (population) with the known damage events within cluster C (subpopulation), only minor differences are noticeable. The estimated parameters of the Weibull distribution models differed only slightly. This may be due to the fact that only four of all known failure events are not part of Cluster C. On the other hand, the failure behavior in relation to the entire fleet (population) shows a clear difference in contrast to that in relation to cluster C (subpopulation). The failure probability in relation to cluster C is significantly higher, due to the smaller size of the sub-population (LEV cluster C fleet) compared to the total population (LEV fleet). For a risk forecast, the failure behavior per cluster can be determined; a comparison of the failure probabilities provides indicators of the sequence in which the clusters are processed in the event of a field measure.

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