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Reliability library using the reliability block diagram method based on field return data

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Within the automotive industry context, knowledge of our product reliability is necessary to remain competitive. Capitalizing on our knowledge from field return data to provide reliability information to development teams is a pillar of our R&D strategy, made more accessible today thanks to digital tools. Predictive reliability is a major discipline of research and development activities because it demonstrates the performance of the systems developed for our customers. The main goal of this paper is to illustrate the process of building a system reliability model using field return data, analyzing failures down to the sub-system level and their specific failure effects. The objective is to create and update a sub-system reliability library using the Reliability Block Diagram (RBD) method, which enhances the precision of assessments of system reliability. The stakes of this project are twofold: Demonstrating predictive reliability that aligns with customer targets early in new project development and Capitalizing on a Sub-system reliability library through the analysis and expertise of warranty return parts.

This approach offers several advantages: Knowing component reliability helps identify the most sensitive sub-systems for implementing improvement solutions and increasing product reliability. It allows for the updating of Failure Mode, Effects, and Criticality Analyses (FMEA) through both qualitative (failure cause and effect) and quantitative (criticality assessment) studies. Historically, meeting customer reliability requirements often demanded significant support from specialists. The RBD approach simplifies this by providing autonomy to project teams via the component reliability library. Teams can use this library to model the system (e.g., a headlamp) and calculate its predictive reliability. The methodology is founded on field return data (REX), where the warranty returns database (parts failing during the warranty period) is the indispensable tool. The quality of the analysis results is directly dependent on the quality of the recorded data, confirming REX's contribution to reliability mastery.

Reliability, FMEA, Reliability block diagram, Field return data, Fault tree analysis

1. Introduction

Within the automotive industry, understanding product reliability is essential to remaining competitive. Leveraging field experience to provide reliability insights to development teams is a pillar of our R&D strategy: an effort made more accessible today through digital tools. Predictive reliability is a key discipline in R&D, as it validates the performance of systems developed for our customers. The purpose of this paper is to demonstrate, through a comprehensive case study, the implementation of a system reliability model based on field experience, analyzed down to individual components and failure modes. The objective is to maintain and update a component reliability library using field data and the Reliability Block Diagram (RBD) method. This approach enhances the precision of reliability assessments by performing them at the component level. The challenge is twofold: first, to demonstrate predictive reliability aligned with customer targets from the very beginning of a project; and second, to capitalize on a component reliability library through technical analysis and expertise regarding warranty return parts. This approach offers several advantages. Understanding component reliability helps identify the most sensitive elements, enabling the implementation of targeted improvements to increase overall product reliability. Furthermore, it allows for the updating of Failure Mode, Effects, and Criticality Analyses (FMEA) through both qualitative (failure causes and effects) and quantitative (criticality assessment) studies. Traditionally, meeting customer requirements for predictive reliability required significant support from specialists. The RBD approach simplifies this process by granting project teams autonomy through a centralized collection of reliability data. Teams can model a system (e.g., a headlamp) using the specific components of a new project to calculate its predictive reliability.

This methodology is primarily founded on Field Return (REX), where the warranty return database (tracking parts that failed during the warranty period) serves as an essential tool. Ultimately, the quality of the analysis depends on the quality of the recorded data, illustrating how field experience is fundamental to mastering reliability.

2. Methodology

The Reliability Block Diagram (RBD) method allows for the functional modeling of a system by assuming that its global functions result from a series (in our case) of elementary functions. Each component of the system is considered independent and performs an autonomous function. The evaluation of the system's reliability is then derived from this functional modelling. Two primary methods can be used to define component reliability:

- Experimental reliability
- Predictive reliability, derived from calculations using industry standards (such as FIDES for electronic components).

Both categories require a precise knowledge of the mission profile for application and an understanding of failure mechanisms to define appropriate tests. To overcome these constraints, component reliability calculations are performed using field experience (REX). In the automotive industry, the extensive availability of warranty return data allows for the calculation of operational reliability and associated parameters, which can then be used to determine predictive reliability under specific conditions.

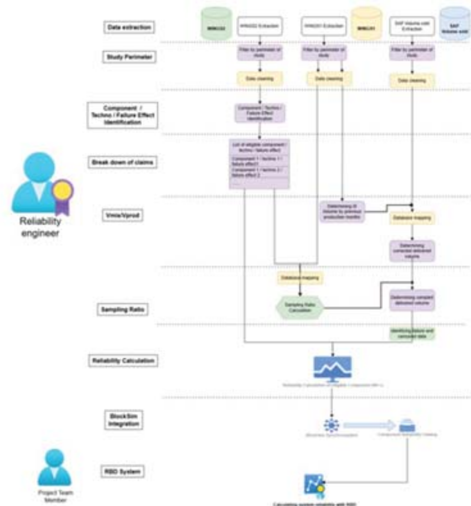

Fig 1: Process description

The specificity of the approach shown in Fig. 1 lies in the standardized process for analyzing warranty return parts. All Valeo sites analyze these parts according to an internal standard. This process identifies the failing component and the failure mode, while distinguishing intrinsic failures (Valeo's responsibility) from extrinsic failures (resulting from misuse). Internal audits ensure this approach is rigorously maintained across the group.

This standardized process is the foundation upon which our approach is applied. All resulting information is integrated into a group-wide cloud database, providing access to all part analyses.

The main challenge to be addressed is that analyses are performed on a sample of the total field returns. This sample varies over time and across different regions where vehicles are sold. Reliable calculations can only be performed by knowing the volume of vehicles in service associated with this sample, which is directly linked to the sampling coefficient. Consequently, the accuracy of the results depends on the sampling methodology, which will be detailed in a specific section.

2.1. *Presentation of warranty return databases*

The available input data consists of customer returns during the warranty period, which typically ranges from 24 to 60 months depending on the manufacturer and the region. This information is centralized for all Valeo sites in a global database known as **WINGS** (Warranty INcidents Getting Solved). This application operates through two independent, integrated databases (see Fig. 2).

Fig 2: WINGS Application

2.1.1 *WINGS 1*

This module aggregates all Original Equipment Manufacturer (OEM) claims. Data is converted from various manufacturer-specific formats into a unified Valeo Standard, ensuring a consistent model across all manufacturers and Valeo sites. The database is updated monthly.

WINGS 1 contains vehicle traceability data and the initial symptoms identified by the technician (see Fig. 3). However, it lacks specific information regarding the faulty component; therefore, it cannot be used for reliability analysis at the component level.

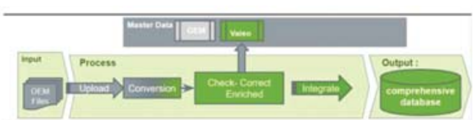

Fig 3: Data loading process in the WINGS 1 application

2.1.2 *WINGS 2*

WINGS 2 is used to monitor the failure analysis process for field returns across all Valeo sites. The analysis results provide comprehensive data, including:

- Vehicle traceability
- Results of diagnostic tests performed to confirm the failure
- Identification of the specific faulty component
- Identification of the failure mode

2.2. *Detailed process description*

The analysis follows the VDA (Verband der Automobilindustrie) standard (see **Fig. 4**), specifically the *Field Failure Analysis & Audit Standard, 2nd revised edition, November 2018.*

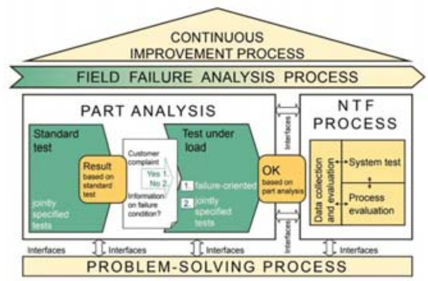

Fig 4: Field Failure analysis process

This study relies primarily on data extractions from WINGS 2, as it provides the necessary details on the failed component and the nature of the defect.

2.2.1 *Extraction of Field return from physical parts*

Database extractions are generated based on specific filters. Each entry in the WINGS 2 database represents a customer complaint and contains several key fields (see Fig. 5).

Fig 5: WINGS2 Extract

- WINGS Claim Link: A direct link to the full claim record within the WINGS system.
- Customer Name: The name of the vehicle manufacturer.
- VIN: An encoded Vehicle Identification Number (to ensure GDPR compliance).
- Customer Part Description: The specific vehicle project code.
- Failure Code: A code defining the component failure or defect.
- Responsibility: Categorized as intrinsic (Valeo's responsibility) or extrinsic (resulting from customer misuse or external factors).
- Production Date: The date the part was manufactured.
- Repair Date: The date the vehicle was repaired.
- Vehicle Sale Date: The date of commissioning (start of service).
- MiS (Months in Service): The duration of the part's use in months.

Detailed definitions for each failure code can be retrieved from the **WINGS Standard list of failures**, which maps all codes to their respective failed sub-components and failure effects.

2.2.2 *Data cleaning*

To prevent biased results, data cleaning is a critical step. It ensures the removal of erroneous, incomplete, or inconsistent data, thereby ensuring the accuracy and reliability of the final analysis. Three primary filters were applied during this stage:

- Project Selection: Filtering specific vehicle project codes to be retained for the study.
- Removal of "No Trouble Found" (NTF): Excluding returns where no defect was detected during laboratory analysis (non-faulty parts).
- Intrinsic Defect Selection: Retaining only failures attributable to Valeo's responsibility (intrinsic defects).

2.2.3 *Definition of the study scope*

The scope of the study is defined by three main criteria:

- Technology: Warranty return data is categorized by project references (specific to a vehicle) and linked to the specific technology of the failed components.
- Temporal Scope: The analysis is based on the production date of the parts to align failure data with the corresponding production volumes over the same period.
- Warranty Duration: Defined as 24 to 60 months, depending on the manufacturer's requirements and the country of delivery.

2.2.4 *Extraction of Valeo sales volume*

Reliability calculations are performed using data from both failed parts and suspended parts (right-censored data). While failed parts are identified through the WINGS 2 database, the number of suspended parts is not directly available.

By definition, suspended parts are those currently "in service" that have not yet failed. The volume in service is derived from Valeo's sales production data using a distribution table (see Fig. 6).

Mois	The percentage of vehicles put into service	Cumulated percentage
0	13.71%	13.71%
1	20.97%	34.68%
2	24.19%	58.87%
3	22.58%	81.45%
4	5.65%	87.10%
5	2.42%	89.52%
6	0.81%	90.32%
7	2.42%	92.74%
8	1.61%	94.35%
12	0.81%	95.16%
14	0.81%	95.97%
17	0.81%	96.77%
18	1.61%	98.39%
19	0.81%	99.19%
24	0.81%	100.00%

Fig 6: Table of the distribution of the delivered volume

This table accounts for the time lag between production and Sale:

- Column 1: Shows the time difference (in months) between the production Month and the service Month (M)
- Column 2: Illustrates the percentage of vehicles put into service relative to the total volume produced in month M-x.
- Column 3: Presents the cumulative percentage of these vehicles.

i	Delivery Month	VVM	VLC
10	02/2021	2376	
9	03/2021	1582	
8	04/2021	2603	
7	05/2021	1392	
6	06/2021	3094	
5	07/2021	2328	
4	08/2021	1631	
3	09/2021	3346	
2	10/2021	3129	
1	11/2021	3163	
0	12/2021	3668	3115
	02/2022	3602	3292
	03/2022	4055	3532
	04/2022	4325	3791
	05/2022	4268	3966
	06/2022	4105	4018
	07/2022	3980	3998

DV : Delivery Volume

Fig 7: Table of the delivered volume

The formular of delivered volume is:

$$DV = \sum_{i=0}^{n} SV_i \times P_i$$

Where DV the delivered volume
SV_i the volume sold at month i
P_i compared to production at the ith month (see fig 6)

2.2.5. *Sampling*

To streamline part analysis and logistics, manufacturers provide suppliers with a representative sample of warranty returns. However, since the exact size of this sample relative to the total population is often not explicitly known, it must be determined using a sampling coefficient.

Calculation of the Sampling Coefficient
The primary challenge of this study lies in precisely estimating the volume associated with failed parts to establish a robust reliability model. While the identification of failed components is well-managed, accessing total volume data presents difficulties:

- Data Availability: Information is not directly accessible; we rely on annual reports comparing the number of analyzed parts (WINGS 2) to the total number of returns (WINGS 1).
- Variability: This coefficient, known as the Yearly Repair Ratio (YoRR), is dynamic and fluctuates based on the manufacturer, the period (typically annually), and the technology being studied.

<u>Methodology:</u> Temporal Projection
The objective is to refine this annual repair coefficient into monthly granularity aligned with the production date. To achieve this, we use WINGS 1 data to analyze the temporal distribution of returns. The method involves creating a pivot table (see **Fig. 8**) containing:

1. The Year of Repair (Columns).
2. The Month of Production (Rows).

	Repair year					
	2021	2022	2023	2024	2025	
Year repair ratio	46%	73%	97%	71%	85%	Monthly Prod ratio
Jan2021	28%	28%	24%	16%	4%	72%
Feb2021	22%	29%	26%	17%	5%	74%
Mar2021	20%	29%	24%	22%	5%	74%
Apr2021	18%	28%	26%	20%	8%	75%
May2021	17%	23%	32%	22%	7%	76%
Jun2021	18%	27%	27%	21%	7%	75%
Jul2021	16%	32%	29%	18%	5%	76%
Aug2021	12%	26%	40%	16%	5%	80%
Sep2021	6%	42%	41%	8%	3%	81%
Oct2021	1%	38%	46%	12%	3%	84%
Nov2021	1%	37%	40%	17%	5%	83%
Dec2021		33%	46%	14%	7%	85%
Jan2022		29%	38%	25%	8%	83%
Feb2022		24%	37%	28%	11%	83%
Mar2022		22%	41%	30%	7%	83%
Apr2022		22%	30%	30%	17%	82%

Fig 8: Distribution of claims ratio per production month for year of repair & Sampling ratio per production month

The calculation follows two logical steps:

- Monthly Production Distribution: For each production month, we determine the percentage of claims occurring across different years. Each row (production month) is normalized to a total of 100%.
- Final Weighting for Each Production Month: The specific coefficient for WINGS 2/WINGS 1 parts is obtained by calculating the sum of the annual repair coefficients, weighted by the annual distribution percentage identified in the previous step.

The formula for the monthly sampling coefficient is:

$$Coef\ MoPR_i = \sum_{y} xi_y \times Coef\ YoRR_y$$

Where xi_y The percentage of the ith production month's returns that occurred in year y
$Coef\ YoRR_y$ is The Year Repair Ratio (WINGS 2 / WINGS 1) for year y

2.2.6 *Reliability calculation tools*

The study utilizes the Reliasoft software suite, a specialized platform for advanced reliability and failure data analysis. Two specific applications are employed:

- Weibull++: Used for Life Data Analysis (LDA). This tool calculates Weibull parameters and determines reliability over specific durations based on failure data.

- BlockSim: Used to build reliability models that evaluate system performance and risks. It facilitates the creation of Reliability Block Diagrams (RBD) and stores component reliability data for the final system compilation.

Based on the previously described pivot table, the data is processed as lifetime data (Months In Service - MIS). This data is treated as right-censored and grouped to define a 2-parameter Weibull reliability model within Weibull++.

To calculate the probability of the system remaining fault-free over a specified duration, the 2-parameter Weibull distribution—the industry standard in automotive engineering—is applied. The model parameters are determined using the Maximum Likelihood Estimation (MLE) method, which is particularly well-suited for datasets with high levels of censoring.

2.2.7 *Synchronization of component reliability calculations in the BlockSim compilation*

Within the Reliasoft suite, once calculations are completed in Weibull++, the results are "published," enabling them to be directly transferred to BlockSim. Once this step is finalized, the Reliability Block Diagram (RBD) can be constructed.

To ensure statistical significance, a minimum threshold of 30 analyzed failed parts per component is required to perform an individual reliability calculation. Components that do not meet this criterion undergo a specific statistical process: they are either integrated into existing blocks or grouped into a single aggregate block representing components with low reliability impact. This block is labeled "Others." One of the project's objectives is to ensure that the "Others" block remains negligible compared to the primary functional blocks in the RBD.

The ultimate goal of this project is to develop a comprehensive reliability library containing all component reliability data. These values are used to populate the RBD and are stored within the application in a dedicated section that serves as the official compilation, as illustrated in Fig. 9.

Fig 9: Example of an extract from the reliability library

3. Results

Initially, reliability studies were performed using the databases of the Valeo sites in Angers (France) and Wuhan (China). The reliability of headlamp sub-components was determined by applying the methodology described in the previous section. Since both studies followed the same logical framework, this section presents the most recent results, specifically those obtained from the Wuhan site.

3.1 *Data cleaning*

- Data cleaning was conducted according to the three primary filters established in the methodology
- Selection of Vehicle Project Codes: Projects were selected based on a data usability assessment.
- Data Usability Criteria: Usability is determined by whether the "MiS" (Months in Service) field is consistently populated for every record associated with a project reference. If the field is sufficiently filled, the data is retained.
- Exclusion of "No Trouble Found" (NTF) Parts: All returns where no defect was detected during laboratory analysis are removed. Records identified as "NTF" in the failure effect field are filtered out.
- Selection of Intrinsic Defects: Only failures attributable to Valeo's responsibility (intrinsic defects) are retained. Extrinsic defects, which fall under the customer's responsibility (e.g., misuse or external damage), are eliminated.

3.2. *Definition of the Study Scope (Wuhan Site)*

When applying the study scope to the Wuhan site results, the following parameters were used.
Temporal Scope: To ensure the production data is both recent and extensive enough for robust Weibull modeling, the selected interval includes headlamps produced between January 2018 and December 2023.
Following this delimitation, the list of the most impacted components among all returns is presented in Fig. 10.

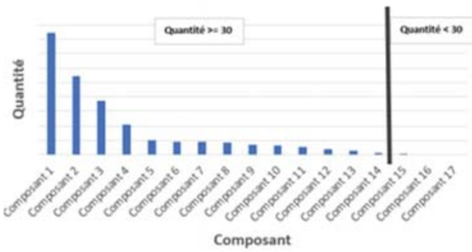

Fig 10: Quantity of removals for each component

The system model (headlamp) is constructed using the Reliability Block Diagram (RBD) method, with components categorized based on the following statistical thresholds:

- Validated Models (>30 returns): Components with more than 30 analyzed failures (C1 to C14) have a statistically validated reliability model (represented by green blocks).
- Marginal Cases (10 to 30 returns): These require expert analysis to validate the component block. Component C15 falls into this category (orange block).
- Residual Category (<10 returns): Components with fewer than 10 failures are grouped into a single aggregate block labeled "Others" (components C16 & C17, purple block).

Fig 11: Example of a component-level Reliability Block Diagram

This independence allows the calculation of system reliability by series system formula.

The next step involves synchronizing the validated data with the BlockSim application. The parameters are saved in the Resource Manager under specific model names. Each model is then associated with a Universal Reliability Definition (URD), which standardizes the reliability characteristics for each component across the library.

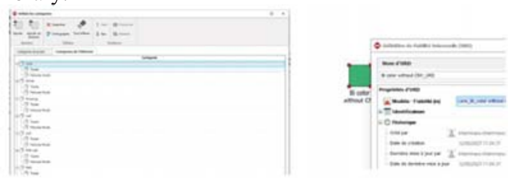

Fig 12: Reliability library extract

This methodology was applied to the Wuhan site data to create a consolidated collection. The final Wuhan data model, shown in **Fig. 13**, comprises 13 independent blocks, reflecting a mature database.

Fig 13: RBD Headlamp model

4. Analysis and discussions

4.1 *Model Validation and Scenario Analysis*

To finalize the reliability diagram, several scenarios may be evaluated. When multiple modeling options exist, a comparative representation is used to plot each option against the reference curve (the actual field reliability of the headlamp).

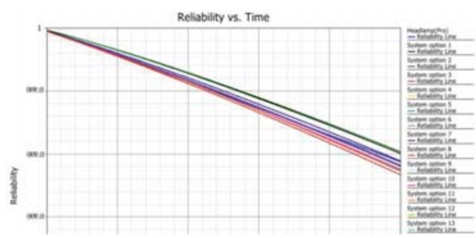

Fig 14: several scenarios of model compared with Headlamp reliability

In this specific case, component C15 has fewer than 30 returns but is close enough to the threshold to warrant investigation. Two scenarios were compared:

- C15 validated as an independent block.
- C15 included within the "Others" block.

The optimal configuration is selected by calculating the Mean Squared Error (MSE) between the scenario curves and the reference curve; the option with the lowest MSE is retained.

4.2 *Reliability Library Update Process*

The collection is updated through two main triggers:

- Temporal Updates: An annual refresh of all component reliability data to integrate the latest field returns.
- Qualitative Updates: Triggered by significant corrective actions. Data is extracted specifically from parts produced after the implementation of the fix. To ensure statistical robustness, a minimum of 18 months of field exposure following the corrective action is required for relevant results.

4.3 *Fault Tree Analysis (FTA) Integration*

Component reliability can also be analyzed by failure effect. The warranty return database allows us to map specific failure modes into a Fault Tree Analysis (FTA). The analysis starts from the Top Event (the undesired effect observed by the customer).

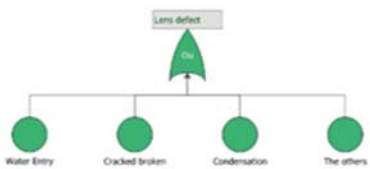

Fig 15: Example of a fault tree for the glass component (Lens)

This data is centralized in the reliability library, allowing R&D teams to update the Occurrence and Criticality ratings in FMEA (Failure Mode and Effects Analysis) documents based on real-world evidence.

4.4 *Limitations of the Approach*

Because the model is built on operational data limited to the warranty period, extrapolating reliability over the vehicle's full lifetime (e.g., 10–15 years) requires caution:

- New Failure Modes: We must ensure that "wear-out" failure modes, which may not appear during the warranty period, are accounted for.
- Extended Analysis: Whenever possible, the study should include data from extended warranty contracts (e.g., 5 years).
- Infant Mortality: The model must distinguish between early-life failures (infant mortality) and constant failure rates to avoid overestimating long-term reliability

5. Conclusion

In conclusion, the methodology presented has been validated through preliminary results derived from the rigorous analysis of field return parts, following the standardized VDA process. Expanding the deployment of this method to larger field databases will facilitate the completion of a comprehensive component reliability library, specifically for the sub-systems that most significantly impact headlamp performance.

However, expert validation remains essential to ensure that secondary failure modes—such as those occurring post-warranty or during wear-out phases—do not compromise predictive accuracy. Defining the temporal validity (or prediction horizon) of these models is therefore a necessary next step. Once finalized, this library will be shared with project teams, granting them greater autonomy in meeting customer reliability requirements and enabling a data-driven approach to updating FMEA criticality ratings based on real-world evidence.

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References

VDA, November 2018, Field Failure Analysis & Audit Standard, 2nd revised edition, Henrish Druck+Medien GmbH

JAKKULA, Balaraju, MANDELA, Govinda Raj, et CH SN, Murthy., 2021, vol. 38, no 3, p. 682-703, Reliability block diagram (RBD) and fault tree analysis (FTA) approaches for estimation of system reliability and availability–a case study. International Journal of Quality & Reliability Management,

Laura Carnevali, Lorenzo Ciani Alessandro Fantechi, April 2021, An Efficient Library for Reliability Block Diagram Evaluation

Shujun Ming, Jul 2025, A new reliability assessment method for complex systems based on RBD and Bayesian networks