Proceedings of the 35th European Safety and Reliability & the 33rd Society for Risk Analysis Europe Conference
Edited by Eirik Bjorheim Abrahamsen, Terje Aven, Frederic Bouder, Roger Flage, Marja Ylönen

doi: 10.3850/978-981-94-3281-3_ESREL-SRA-E2025-P7408-cd

Application of Monte Carlo Simulation in Modeling the Lifetime of Industrial Components

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This paper explores the application of Monte Carlo Simulation (MCS) to model the lifetime of industrial components, specifically focusing on a contactor commonly used in automation systems. The study emphasizes the challenges posed by the variability in system performance and the need to incorporate expert knowledge for accurate modeling. Using expert data, MCS is employed to simulate different scenarios and determine a probabilistic distribution that reflects the uncertainties in component lifespan. The analysis reveals that factors such as temperature, environmental conditions, and switching frequency have significant impacts on the failure rate of the component, thereby influencing its reliability. The results demonstrate the effectiveness of MCS in providing a more precise estimation of component lifetime, offering valuable insights for maintenance planning and operational decision-making. The study concludes that incorporating Monte Carlo methods into reliability assessments enhances the ability to manage risk and optimize system performance, ensuring safer and more efficient operation of industrial systems.

Keywords: Monte Carlo Simulation, industrial reliability, component lifetime, expert knowledge, probabilistic modeling, failure rate

1. Introduction

This study focuses on the application of Monte Carlo Simulation (MCS) to model the lifetime of industrial components, based on data obtained through an expert elicitation process. The choice of this technique is justified by its ability to deal with the variability inherent in industrial systems, where component failure can be influenced by unpredictable factors. The approach allows simulating multiple scenarios, including positive and negative stressors, and obtaining a probabilistic distribution that better reflects operational uncertainties.

In this context, this paper addresses the practical application of MCS to estimate the time to failure of an industrial contactor, a component widely used in global automation. By collecting data from experts and adjusting an appropriate probabilistic distribution, the simulation seeks to accurately represent the component's life expectancy, providing support for decision-making in the management of maintenance and operation of industrial systems.

Although Monte Carlo Simulation is a common tool in reliability analysis, this study offers a novel approach by integrating expert elicitation and modeling with both environmental and operational stressors. This methodology enables a more accurate evaluation of the uncertainty and variability associated with factors affecting component lifespan. Additionally, the replicability of this method to other industrial equipment types enhances its applicability within reliability engineering. Consequently, this research provides a valuable framework for supporting decision-making in maintenance and operational planning.

The paper is structured into the following main sections. The first section presents a literature review, highlighting the main studies and advances related to expert data elicitation and the application of MCS in industrial scenarios. Then, in the methodology section, the steps and methods used are described, from data collection to stressor modeling and simulation implementation. The results of the analysis, presented in the following section, include the estimation of the contactor's service life and the identification of critical factors that influence its reliability. Finally, the discussion and conclusions address the implications of the results and suggest strategies for practical application and future studies.

2. Literature review

According to Clemen and Reilly Clemen and Reilly (2001), effective elicitation requires a structured approach to ensure that the information provided by experts is both accurate and useful. They emphasize that the process should minimize the influence of cognitive biases and ensure that estimates are consistent and evidence-based. The work of O'Hagan et al. O'Hagan et al. (2006) is relevant in this context, as it introduced formal methods for probability elicitation, including techniques for combining multiple expert opinions and analyzing associated uncertainties.

Recently, the literature has advanced in understanding the challenges and methods to improve the accuracy of probability estimates. Fischhoff and Schoch-Spana Fischhoff and Schoch-Spana (2020) explored the application of Bayesian modeling techniques for the integration of expert opinions, offering a robust approach to combine qualitative and quantitative information. They argue that Bayesian modeling can help to address uncertainty and variability more effectively, providing a more reliable estimate than traditional methods. Furthermore, Morss et al. Morss et al. (2008) discussed the impact of heuristics and biases in probability elicitation and proposed strategies to mitigate these effects, such as the use of iterative feedback techniques and continuous revisions of estimates, which have shown promise in improving the quality of estimates.

Several studies highlight the application of Monte Carlo Simulation (MCS) in a variety of practical contexts. Some studies have used the Kinetic Monte Carlo technique to model complex processes in semiconductor manufacturing, such as implantation, annealing, and epitaxial growth of semiconductor devices Martin-Bragado et al. (2018). This study showed how MCS can simulate the evolution of defects in silicon, validating the results with experimental data. In the pharmaceutical industry, it was possible to verify the application of MCS in conjunction with genetic algorithms to design distribution networks under demand uncertainty Izadi and Kimiagari (2014). The study allowed a reduction in supply chain costs by 14%, providing a robust framework for allocating customer demands, even in the face of unpredictable variations, such as epidemic outbreaks. In addition, other studies explored the use of MCS in risk assessment in project schedules. A probabilistic model translated project characteristics into schedule risk bounds, demonstrating its effectiveness on large-scale projects McCabe (2003).

3. Method

3.1. *Distribution reference without considering stressors*

Recognizing the uncertainty inherent in the sequencing of this component, an elicitation process was conducted with experts, aiming to capture the variations and uncertainties related to this value. A crucial point of the method is that the data provided by the experts should reflect nominal information, that is, without the influence of stressors such as environmental factors or operational conditions. This aspect was repeatedly highlighted as essential to ensure the validity of the process.

For the elicitation, five experts in the areas of electrical engineering, automation and system reliability were consulted. Each expert had a distinct profile, and each was assigned a weight based on their professional experience, specific knowledge domain and the relevance of their contributions to the scope of the study. These weights were used to reflect the reliability and influence of each expert on the final results. However, it is recognized that the complete elimination of biases and heuristics during elicitation processes is challenging, since cognitive biases are inherent to human behavior, even among experienced experts. Therefore, the possible residual influence of these biases was considered in the analysis and interpretation of the results. The main biases and heuristics observed and mitigated in the study include:

- Anchoring: Tendency to rely excessively on initial information provided.
- Availability Heuristic: Evaluation based on examples easily accessible to memory.
- Confirmation Bias: Search for information that reinforces previous beliefs.
- Sunk Cost Effect: Tendency to maintain previous decisions even when they become disadvantageous.
- Hindsight Bias: Overestimation of the predictability of past events.
- Abilene Effect: Group decisions that contradict individual preferences.
- Primacy and Recency: Disproportionate influence of the first and last information presented.

Biases and heuristics have been widely addressed in studies, especially in the context of decision-making in clinical settings. For example, in a study on medical decision-making, it was identified that health professionals often suffered from biases such as anchoring bias, where they fixated excessively on initial diagnoses, which led to subsequent decisions based on these first impressions, ignoring other possibilities Featherstone and et al. (2020).

Another bias observed was availability bias, in which clinicians tend to rely on recent or easily remembered cases rather than considering more comprehensive data or less common conditions. To mitigate the effects of these cognitive biases, approaches based on structured decision-making practices have been implemented, such as the use of systematic analytical tools, the implementation of peer reviews, and the designation of roles to challenge assumptions. These strategies aim to promote objective assessment, minimizing the influence of cognitive heuristics that can distort the decision-making process. The use of standardized protocols, for example, helps to reduce the influence of biases such as confirmation and anchoring, while peer review promotes independent critical analysis, essential for the validation of hypotheses and decisions in the clinical context and in clinical trials McGowan (2023).

These approaches helped define the relevance of each expert's response and, above all, to qualify whether the data provided could be used as reference values.

Regarding elicitation, it was conducted by requesting specific quantiles of a probability distribution, reflecting the uncertainty perceived by the experts in relation to the real value of B10. Three main questions were formulated for each expert, directly and with the possibility of only one simple answer, corresponding to the 25%, 50% and 75% quantiles of the real distribution. The answers obtained served as a basis for the subsequent stages of analysis.

From the experts' responses, exponential distribution curves were determined that represent the estimate of the B10 value for each expert. Each curve was parameterized based on the parameter λ, which represents the expected failure rate per operating cycle, inversely associated with the expected useful life of the component.

From the individual exponential curves, a weighted average of the failure rates (λ) obtained was calculated, using the weights previously assigned to each expert. This average was then used to determine a consolidated estimate of the MTBF (Mean Time Between Failures).

Based on the normal distribution parameterized by the MTBF, an initial distribution of the failure rate for the component was generated. This failure rate was subsequently adjusted to incorporate the effects of environmental factors, temperature, and switching frequency.

3.2. *Stressors*

3.2.1. *Temperature*

The effect of temperature on the contactor failure rate was modeled based on the Arrhenius equation, which relates the operating temperature to the probability of failure. To this end, the activation energy (E_a), a constant obtained from component-specific tables, and the average operating temperature (T_o), which is estimated based on the geographic region of use of the contactor, are considered.

The uncertainty around T_o was represented by a normal distribution with mean μ_{T_o} and standard deviation σ_{T_o}, reflecting the possible climatic and environmental variations in the different installation regions. Thus, the temperature factor was determined by the Eq. (1):

$$f_{\text{temp}} = \exp\left(\frac{E_a}{k}\left(\frac{1}{T_{\text{ref}}} - \frac{1}{T_o}\right)\right) \tag{1}$$

Where:

- E_a is the activation energy (eV);
- k is the Boltzmann constant;
- T_{ref} is the reference temperature in Kelvin;
- T_o is the average operating temperature, considered a random variable with uncertainty.

3.2.2. *Environmental Factor*

The influence of environmental conditions was modeled based on Table 4 of IEC 61709:2017 and elicitation of experts, who categorized the operating environments into three main situations International Electrotechnical Commission (2017):

- **E1**: Protected and stationary conditions, considered more favorable;
- **E2**: Stationary conditions without protection;
- **E3**: Portable or non-stationary conditions, associated with the greatest environmental impact.

The experts assigned probabilities of occurrence for each of these categories (p_{E1}, p_{E2}, p_{E3}), enabling the construction of a probabilistic model for the environmental factor (f_{amb}). This factor was represented as a discrete variable, whose distribution reflects the expected proportion of each environmental scenario.

3.2.3. *Usage Factor (Switching Rate)*

The contactor usage factor was modeled based on the switching cycle frequency, represented as a continuous random variable. According to the experts, the switching rate (S_{rate}) follows a normal distribution with mean $\mu_{S_{\text{rate}}}$ and standard deviation $\sigma_{S_{\text{rate}}}$, reflecting the different typical usage levels of the component.

The usage factor was determined by the ratio between S_{rate} and a reference rate ($S_{\text{rate,ref}}$), expressed as in Eq. (2):

$$f_{\text{srate}} = \frac{S_{\text{rate}}}{S_{\text{rate,ref}}} \tag{2}$$

where $S_{\text{rate,ref}}$ represents the standard usage of one cycle per hour.

3.3. *Stressor Integration*

The factors f_{temp}, f_{amb} and f_{srate} were incorporated into the model to correct the contactor failure rate as a function of operating conditions. The integration of these factors allows capturing the combined influence of temperature, environment and frequency of use, providing a comprehensive view of the component behavior in different operating scenarios.

3.4. *Monte Carlo simulation*

Monte Carlo simulation was used to model the uncertainty associated with the corrected failure rate of the industrial contactor. This method allows the incorporation of previously identified stochastic variables, generating probabilistic distributions that represent realistic operating scenarios.

For the simulation, the parameters established in the previous stages of the study were used as input variables, including environmental, temperature, and usage factors, in addition to the accumulated operating time. These factors were combined to adjust the initial failure rate, as per Eq. (3):

$$\lambda_{\text{corrected}} = \lambda \cdot f_{\text{temp}} \cdot f_{\text{amb}} \cdot f_{\text{srate}} \tag{3}$$

Based on this adjusted rate, the cumulative probability of failure was estimated using the exponential reliability function in Eq. (4):

$$P_{\text{failure}}(t) = 1 - \exp(-\lambda_{\text{corrected}} \cdot t) \quad (4)$$

The model was implemented using the `mc2d` library in the R language, configured to perform $10,001$ iterations. During each iteration, the input variables were sampled from their respective distributions, allowing the propagation of uncertainties through the model.

The simulation structure ensured that all adjustment factors were integrated in a consistent manner, preserving the probabilistic characteristics of the input variables and allowing a detailed analysis of their influence on the contactor reliability. Graphs and distributions were generated as outputs of the process, but their interpretation will be presented later, in the chapter dedicated to the results.

4. Results

Considering the elicitation and the weights assigned to each expert, the *MTBF* was estimated as a Gaussian distribution with a mean of 1,470,000 cycles and a standard deviation of 209,120 cycles. This estimate reflects the expected useful life of the contactor under normal operating conditions, being the starting point for subsequent reliability analyses.

4.1. *Bias and Heuristic Treatment*

Bias and heuristics were addressed using a structured approach that included the selection of highly qualified experts and the application of statistical techniques to adjust the responses collected. During elicitation, the question structure was focused on obtaining specific quantiles, which helped to minimize the influence of anchoring or other cognitive biases on the estimates provided.

In addition, the experts' responses were weighted according to their experience and relevance, ensuring that the most consistent contributions had the greatest influence on the final results. Throughout the process, reviews were conducted to identify inconsistencies or evidence of distortions in the data, allowing adjustments to be made whenever necessary to ensure greater impartiality.

Despite these precautions, it is recognized that complete elimination of bias is practically unfeasible due to the subjective nature of human decision-making. Thus, the results presented consider possible residual influences and were interpreted with this caution in mind.

4.2. *Contactor Reliability Analysis*

Based on the Monte Carlo model and the integration of adjustment factors, the results indicate the cumulative probabilities of failure for different operating times and environmental scenarios. The generated distributions reflect the uncertainty associated with the modeled parameters, allowing a detailed assessment of the most critical scenarios. These analyses are essential to guide decisions on preventive maintenance and component replacement, promoting greater operational reliability.

The graphs show the dispersion of the simulated values, as well as the relative influence of each factor considered in the model. These data will be presented and discussed in the next section.

The graph in Figure 1 shows the evolution of the probability of contactor failure over time, considering the environmental factors, usage rate and temperature conditions incorporated into the model. This curve was generated from Monte Carlo simulations, using the exponential reliability function, which relates the corrected failure rate and the time of use.

In Figure 2, it is possible to observe the increasing trend of the accumulated probability of failure as the operating time increases, indicating the progressive degradation of the component. The distribution reflects the uncertainty in the input parameters, showing a probabilistic behavior that captures both more conservative and extreme scenarios.

Table 1 presents a summary of the main results obtained from the Monte Carlo simulation performed to evaluate the system reliability under different operating conditions. It provides information for the reliability analysis, including the corrected MTBF, the failure rate, environmental and temperature factors, and the adjusted failure rate.

The corrected MTBF, with an average of approximately 544,000 hours, represents the expected average time of system operation before failure occurs, considering actual operating conditions. This value is accompanied by the average failure rate, which is 1.84×10^{-6} failures per hour, and provides a quantitative metric of the system's reliability over time. These two indicators are essential for planning maintenance strategies and projecting the system's useful life, since they reflect the expected frequency of failures based on operational and environmental conditions.

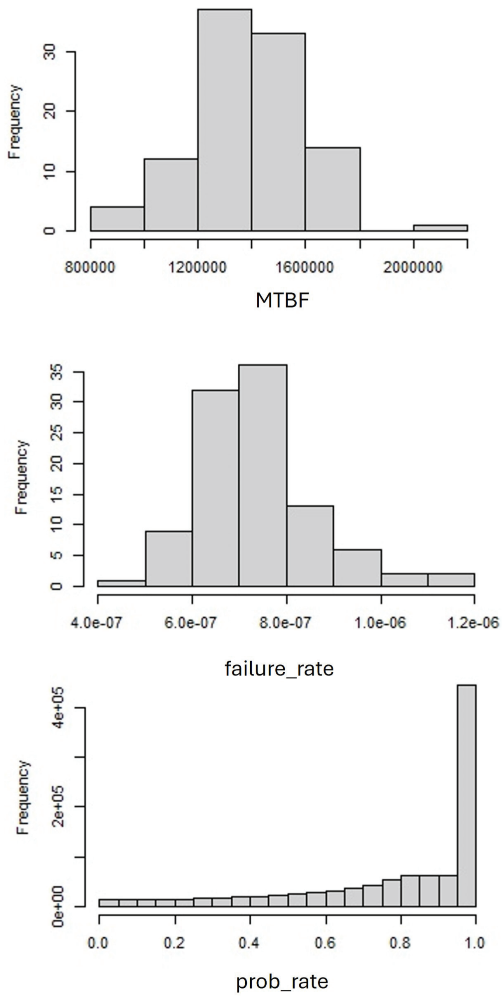

Fig. 1. Graphs generated by the simulation: *MTBF* at the top, failure rate in the center and failure probability at the bottom.

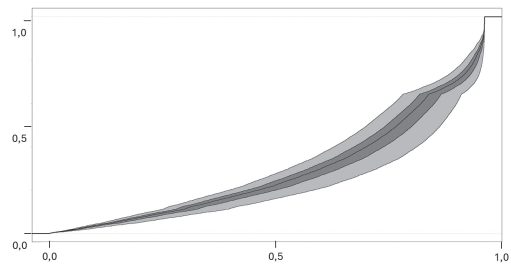

Fig. 2. Cumulative failure probability Fn(x)

Table 1. Summary of simulation results considering 10% and 90% percentiles

Parameter	Mean	Median	10%	90%
Elicited MTBF (10^3h)	1.442	1.451	1.183	1.629
Environmental Factor	1.26	1.00	1.00	2.00
Temperature Factor	1.38	1.00	1.00	2.44
Adjusted Failure Rate (10^{-6}/h)	1.84	1.42	0.89	3.02
Adjusted MTBF (10^3h)	0.544	0.704	0.401	0.976

Furthermore, environmental and temperature factors play a crucial role in assessing reliability, as they indicate how external conditions impact system performance. The environmental factor, with an average of 1.26, suggests that, on average, the operating environment increases the system failure rate by 26%. This factor ranges from 1.00, indicating no significant impact, to 2.00, representing more challenging environmental conditions. The temperature factor, with an average of 1.38, implies that temperature has an average effect of 38% on the failure rate. This factor can range from 1.00 (no impact) to 2.44, highlighting the need for thermal control to ensure system durability.

When combined, these environmental and temperature factors result in the adjusted failure rate, which, with an average of 1.84×10^{-6} failures per hour, provides a more realistic estimate of system reliability under specific operating conditions. The adjusted failure rate value exhibits significant variation, with 10th to 90th percentiles ranging from 0.89×10^{-6} to 3.02×10^{-6} failures per hour, reflecting the different scenarios that the system may face. These data are essential for a detailed reliability analysis, as they allow the adjustment of maintenance strategies and the efficient management of the system life cycle.

These parameters, calculated in the simulation, provide valuable information for assessing system reliability and for developing effective failure mitigation strategies.

It is important to highlight that the proposed model can be adapted to various industrial scenarios, enabling engineers and decision-makers to obtain probabilistic reliability estimates for different components. Although this study does not include a specific case study, the methodology can be applied to real-world data in future research, allowing for empirical validation of the results. The proposed framework facilitates risk analysis in contexts where historical failure data are limited or incomplete, providing a valuable tool for generating more accurate reliability estimates and supporting strategic maintenance planning.

5. Discussion

The results obtained from the MCS provide a detailed view of the MTBF behavior and the probability of failure, considering the operating conditions and environmental factors. The graphical analysis and the presented data reveal important points about the reliability of the evaluated system.

The MTBF distribution presents an average indicating that the system has reliable performance under ideal conditions. The failure rate, inversely proportional to the MTBF, presents average values consistent with the expected reliability. However, correction for the influence of environmental factors, temperature and intensive use increases the corrected failure rate significantly, highlighting the impact of these external variables.

The failure probability graph shows how operating time directly affects system reliability. The curve obtained demonstrates an exponential growth in the failure probability over time, in accordance with the adopted reliability model. The results show that, under severe operating conditions, there is a considerable increase in the failure probability, which reinforces the importance of mitigation strategies, such as preventive maintenance and control of environmental conditions. This analysis can be verified by a second elicitation moment *a posteriori*.

Environmental and temperature factors were modeled in a realistic manner using expert-based distributions. The analysis revealed that portable or non-stationary equipment is more prone to failure due to the increase in the environmental factor and the corrected failure rate. Similarly, high operating temperatures resulted in an exponential increase in the temperature factor, highlighting the sensitivity of the system to thermal variations.

Additionally, the rate of use showed a significant impact, with more intense operating cycles resulting in an increased probability of failure. This finding suggests that reducing continuous use may be a viable strategy to extend equipment life.

Therefore, the modeling and results presented are consistent with theoretical expectations and help to understand how different factors affect system reliability. This information can be applied in planning maintenance strategies and in developing new systems with greater robustness against adverse operating conditions.

6. Conclusions

This study used expert data elicitation to establish the parameters needed to model the reliability of systems under different environmental and usage conditions. Based on these parameters, such as MTBF, failure rate, environmental, thermal and usage factors, a Monte Carlo simulation was implemented to evaluate the probability of failure over time. The results demonstrated the relevance of external variables, such as temperature and operating intensity, in increasing the corrected failure rate and reducing system reliability. The analysis revealed the importance of mitigation strategies, such as preventive maintenance and control of operating conditions, to minimize failure risks.

As limitations of the study, although the methods used allowed a robust evaluation, the dependence on expert data elicitation introduces possible biases and heuristics that can affect the results, as explained by overconfidence in judgments or insufficient representativeness of the modeled scenarios. In addition, simplifications made in the models, such as the assumption of independence between factors, may not fully reflect the complexity of the system under all real conditions. For future work, it is recommended to use machine learning methods to refine estimates and reduce biases in elicitation. It is recommended that the model be applied to real industrial systems, accompanied by the collection of empirical data to assess the accuracy of the generated estimates. Additionally, comparing the proposed approach with other methodologies, such as deterministic models, could provide further insights into its robustness and applicability. Expanding the study to include other operational scenarios (such as the additional consideration of technical factors - voltage, electrical current and electrical stress) and critical variables can also improve the generalizability of the results. Finally, validating the models through empirical data from field failures is essential to consolidate the applicability of the conclusions in the industrial context.

Acknowledgement

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) – Finance Code 001.

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