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RESEARCH ARTICLE

Impact of Parameter Uncertainties on Power Electronic Device Lifetime Predictions

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ABSTRACT Properly addressing uncertainties in reliability analysis is essential for realistic lifetime predictions of power devices. This paper investigates parameter uncertainties on the lifetime estimation of power devices using an empirical lifetime model and Monte Carlo simulations. Key parameters such as junction temperature swings (ΔT_j), minimum junction temperature ($T_{j,\min}$), and lifetime model constants are analyzed for their impacts on lifetime outcomes. Sensitivity analysis reveals significant effects from variations in parameters like β_1 and ΔT_j on the expected lifetime and its variability. Simultaneous variations across all parameters further highlight the dominant influence of β_1 on lifetime predictions. The analysis suggests that a 5 % uncertainty margin appears to offer a balanced trade-off between realistic lifetime estimations and predictability. This Study underscores the importance of considering parameter uncertainties for precise reliability evaluations. It addresses a critical gap by examining the rationale behind commonly assumed 5 %, and 10 % uncertainty margins in lifetime modeling. By systematically evaluating these margins' impacts on key reliability parameters, the study provides a framework for selecting reasonable assumptions based on physical insights and variability analysis, advancing the reliability modeling of power devices.

INDEX TERMS Reliability, uncertainty analysis, lifetime models, power device, lifetime estimation.

I. INTRODUCTION

The reliability of power electronics systems is a critical factor in ensuring the safe and efficient operation of modern electrical infrastructure. Failure of these systems can lead to significant costs and safety hazards, making reliability assessment a vital aspect of the design and development process [1], [2]. Power devices, such as IGBTs and MOSFETs, play a crucial role in these systems by switching and regulating power flow [3], [4]. Their reliability directly impacts the performance of power converters, which are extensively used in applications such as electric vehicles, renewable energy systems, and industrial automation. Ensuring the reliability of these power devices is therefore important for minimizing failures, reducing maintenance costs, and ensuring uninterrupted service.

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Power converters, which utilize power devices to control energy flow, are especially vulnerable to operational failures, significantly influencing the overall system's reliability [3]. Studies show that power switches and capacitors are the components most susceptible to failures in power electronic interfaces [4], [5], [6]. Thermo-mechanical stresses, resulting mainly from temperature variations, are a major cause of these failures and greatly increase the likelihood of wear-out mechanisms such as bond-wire fatigue and solder degradation in power devices [7], [8]. These stresses are induced by thermal cycles caused by load changes, switching behavior, and environmental factors, which lead to repeated heating and cooling of power devices. This cycling creates thermo-mechanical stress due to the varied thermal expansion coefficients of different materials in power devices, leading to degradation over time [8]. The thermal cycles impacting power devices can be categorized into fundamental, long-term, and short-term cycles. Fundamental thermal cycles are associated with load variations, transient temperature differences are influenced by switching frequency, and long-term cycles are primarily affected by environmental factors [7], [8]. Power cycling experiments have demonstrated that long-term thermal cycles lead to fatigue in the thermal interface material and DBC-attach solder, while short-term cycles are responsible for wear in bond wires and die-attach solder [7], [9], [10]. These wear-out mechanisms significantly contribute to the degradation of power devices and thus shorten their lifetimes.

Conventional reliability data, like those in standard handbooks, frequently make the assumption that failure rates are constant and may not take into consideration the wear-out mechanisms that are common in power semiconductors. It is essential to take into account the effects of numerous stressors, such as temperature and humidity, which might hasten the failure processes, for a more precise reliability prediction [11]. Although generic reliability data, such as those included in the FIDES guide, might offer valuable insight, they frequently lack the detail required for individual components and technologies. Because of this, it is still difficult to estimate the reliability of the system realistically without conducting an in-depth component-level analysis [11], [12].

To predict the expected lifetime of power devices, a comprehensive reliability assessment framework is required. This framework often involves empirical lifetime models that account for failure mechanisms, including bond-wire fatigue and solder degradation [13], [14]. Initially, the reliability of power devices was determined through deterministic calculations of time-to-failure based on specific loading profiles [15]. Although these methods provided a foundational understanding, they were limited by their inability to account for the inherent uncertainties and variabilities present in real-world applications, such as those arising from material inconsistencies and operational stresses. To overcome these limitations, researchers have increasingly turned to probabilistic approaches that incorporate statistical evaluations, such as Monte Carlo simulations. Monte Carlo simulations have become a popular technique for evaluating power electronics reliability. By modeling stress parameters such as thermal cycles and lifetime model parameters with particular distributions, this technique enables the use of different samples in multiple simulations [16], [17]. The lifetime distribution can be determined by computing the cumulative damage in each sample; this distribution frequently resembles a Weibull distribution with a non-constant failure rate [18]. With this approach, component lifetimes under real-life situations are represented with more accuracy.

Several empirical lifetime models, such as the LESIT, CIPS 2008 (Bayerer), corrected CIPS 2008, and Skim models, have been developed for predicting the lifetime of power devices, each based on wear-out failure mechanisms [19], [20]. These models, detailed in studies [13], [14], [20], [21], [22], vary in their approach and accuracy. These models, which depend on accelerated power cycle studies, include several factors that affect power component reliability. During these tests, these critical factors are carefully considered.

Uncertainties in real-world scenarios originate from variations in lifetime model parameters and inconsistencies in the component manufacturing procedure. These uncertainties must be taken into account when assessing the reliability of the components [11]. A popular statistical technique called the Monte Carlo method is used to address these uncertainties. With this approach, the reliability of a component can be carefully and realistically assessed in a variety of scenarios [23]. The choice of key variables influenced by real-world conditions, along with the extent of their variability, can significantly affect the lifetime estimates for power devices. However, many studies assume fixed uncertainty margins, such as 5 % or 10 %, for parameter variations without providing a rationale for these choices [11], [24], [25], [26], [27]. This can lead to overly conservative or overly optimistic reliability predictions, which may not reflect real-world conditions. To address this gap, this study systematically investigates the impact of different margins on lifetime model parameters, particularly the Weibull parameters α (scale factor) and β (shape factor), to derive reasonable assumptions for parameter uncertainties based on physical and operational insights [46].

This paper explores the influence of these parameters and their associated uncertainties on the lifetime model, with a focus on identifying the most significant sources of uncertainty. To carry out this investigation, we perform a load-based reliability assessment of power devices tailored to a specific application. In this case, the application is an EV fast charger, for which the reliability of a full-bridge power converter has been previously investigated in [28] and [29]. However, the primary objective of this study is to assess the impact of parameter variations on lifetime estimation. This methodology is broadly applicable to any application that utilizes similar lifetime models for assessing the reliability of power devices.

The following sections represent the framework of this paper. In Section II, firstly, the power device number of cycles to failure based on the different junction temperature cycles is predicted by utilizing an empirical lifetime model without considering uncertainties, and also information about the reliability function was provided. Then in subsection II-B, we delve further into the Monte Carlo study of parameter uncertainties in power device reliability, examining the impact of varying both single and all parameters on lifetime estimations of power components, respectively. The conclusions from the data are presented in Section III.

II. RELIABILITY OF POWER DEVICES BY CONSIDERING UNCERTAINTIES

A. LIFETIME ESTIMATION FRAMEWORK

In recent years, the strategy of predicting device lifetime based on mission or load profiles has gained popularity for reliability analysis. Despite extensive research on mission profile-based reliability assessments across various applications such as PV, wind energy, drivetrain technologies, aerospace, and onboard chargers, a significant research gap remains in studying reliability under specific battery load conditions in DC fast chargers [5], [7], [8], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41]. Within the scope of EV fast-charging systems, the converters endure short spikes of high-current loads to expedite the charging process [42]. This rapid charging is followed by a cooling phase, which subjects the power electronic components to thermal cycling. This thermal cycling, resulting from rapid heating and cooling, can accelerate wear and lead to degradation through mechanisms such as thermo-mechanical fatigue. Consequently, these stresses may shorten the components' lifetime and perhaps result in wear-out failures [28], [29], [43], [44]. So, analyzing the reliability of power devices in these applications is of importance [28]. For this reason, [28] investigated the reliability of power devices and finally, the reliability of power converters in EV fast chargers.

In this paper, we assumed DC fast chargers as the application context for our analysis, referencing prior work in [28], which provides a foundation for assessing the reliability of power converters in EV fast chargers. While our contribution lies in systematically exploring how parameter uncertainties influence lifetime predictions. Although the focus of this study is not on specific applications or load conditions, the methodology presented here is broadly applicable to other applications that utilize similar lifetime models for evaluating the reliability of power devices.

Since temperature data of components is an essential input in the power device lifetime estimation process, this data is used to calculate the power semiconductors' number of cycles to failure (N_{f}) employing empirical lifetime models [13], [14]. Based on [13], [19], [28], [29], and [43], the LESIT model tends to overpredict the number of cycles to failure in situations involving long-term heating, as it does not account for the duration of thermal cycles, which is a critical factor for DBC solder joint fatigue. Conversely, the CIPS model and its corrected version can provide more accurate estimates in cases where DBC solder attach failure is predominant, as they incorporate the effect of the temperature swing duration [14], [28], [29], [43]. Thus, it is crucial to select a lifetime model that aligns with the specific thermal cycle characteristics or the application at hand, ensuring it accurately reflects the relevant failure mechanisms [29], [43], [44].

In EV fast chargers, the DBC-attached solder of power semiconductors can be susceptible to thermal cycles due to the longer temperature durations (t_{on}) [28], [29], [43]. The original CIPS model tends to overestimate the number of cycles to failure when the heating time is longer [28], [43]. This overestimation occurs because the failure of the DBC solder connection typically happens shortly after the heat reaches the baseplate, signaling the device's end of life [28], [29], [43]. So the more appropriate model for EV charging applications can be the corrected CIPS lifetime model, which is employed to determine the number of cycles to failure [28], [29], [43]. Therefore, this study uses this model to investigate parameter uncertainties in this model [43]. The CIPS and the corrected edition are presented in (1) and (2), respectively [14], [20], [21]:

$$N_{\mathrm{f}} = A \Delta T_{\mathrm{j}}^{\beta_1} t_{\mathrm{on}}^{\beta_3} I^{\beta_4} V^{\beta_5} D^{\beta_6} e^{\left(\frac{\beta_2}{T_{\mathrm{jmin}}+273}\right)} \tag{1}$$

$$\frac{N_f(t_{\mathrm{on}})}{N_f(1.5)} = \begin{cases} 2.25 & \text{if } t_{\mathrm{on}} \leq 0.1\, s, \\ \left(\frac{t_{\mathrm{on}}}{1.5}\right)^{-0.3} & \text{if } 0.1 < t_{\mathrm{on}} < 60\, s, \\ 0.33 & \text{if } t_{\mathrm{on}} \geq 60\, s. \end{cases} \tag{2}$$

In [14], the values of the variables A, and $\beta_1 - \beta_6$ are displayed. In addition, it is assumed that the bond wire diameter (D), current per bond wire (I), and voltage range ($V/100$) are $250\, \mu m$, $20\, A$ and $9\, V$. Moreover, t_{on} is the heating time of the device, which is related to the EV fast charger's load profile, in this study.

Since the lifetime estimation of devices in fast-charging applications has been conducted in [28], [29], and [44], this paper focuses specifically on the impact of uncertainties on lifetime estimation. Therefore, without specifying a particular converter type in the application, this study assumes that the assessment approach can be generalized across applications using the same lifetime models. Therefore, it is assumed in this study that the power devices used in the converters of EV fast chargers experience different junction temperature swings at a fixed minimum junction temperature ($T_{\mathrm{j,min}} = 25°\mathrm{C}$) based on the EV battery charging load, with each charging session assumed to have a heating duration of 60 minutes. Consequently, the number of cycles to failure (N_{f}) for these power devices is estimated, as shown in Table 1.

TABLE 1. Number of cycles to failure at different junction temperature differences.

ΔT_j	60°C	80°C	100°C	120°C	140°C
N_f ($\times 10^3$)	370.83	104.1	38.859	17.371	8.7941

These results provide a baseline reference for understanding how different levels of junction temperature swings affect device lifetime under nominal conditions. However, it should be mentioned that the estimated N_{f} are not realistic on their own due to the uncertainties in real life. Their function is to demonstrate the deterministic output of the lifetime model prior to incorporating variability. So, at this stage, the Monte Carlo simulation should be taken into account for a suitable reliability study by considering two main categories of uncertainty: uncertainties arising from production variances in devices and uncertainties in the parameters of the lifetime model. For example, in the manufacturer's datasheet, the changes in IGBT parameters—such as the on-state voltage ($V_{ce,on}$)—are stated, along with typical maximum and lowest values. Since variations in on-state voltage have a direct impact on the IGBT conduction losses, which in turn affect T_j and ΔT_j. Therefore, the reliability analysis should account for the uncertainties in these parameters [11], [14].

To calculate the overall cumulative damage for power components, Miner's rule [45] is used. As a power device experiences damage from the accumulated impacts of thermal cycles, which is given by (3), [45]:

$$D = \sum_{i=1}^{n} \frac{n_i}{N_{f_i}} \tag{3}$$

where N_{f_i}, the number of cycles to failure was computed from the lifetime model, and n_i, is the number of thermal cycles in a year, which corresponds to the i_{th} temperature swing. It should be noted that the daily number of thermal cycles, representing the daily charging sessions in EV charger applications [28], is assumed to be 15 sessions in this study.

Next, using Equation (4), the power component's end-of-life is determined, shown by L_c (in years). The variable D shows the accumulated damage to the component. An estimate of the IGBT module's lifetime is obtained by accumulating D until it reaches a value of 1.

$$L_c = \frac{1}{D} \tag{4}$$

To estimate the reliability of the power device, probability distribution functions are used. These functions describe the likelihood of different failure times, enabling engineers to predict and enhance system reliability. The Weibull and normal (Gaussian) distributions are two often utilized distributions in this subject. The Weibull distribution is especially versatile, capable of modeling increasing, constant, or decreasing failure rates based on its shape parameter (β) [46]. On the other hand, when failure times are symmetrically distributed around a mean value, the normal (Gaussian) distribution is employed. Therefore, when considering wear-out failures, the Weibull distribution is the function that is most recommended. The probability density function (PDF) of the Weibull distribution is expressed as 5, [46]:

$$f(t) = \frac{\beta}{\alpha}\left(\frac{t}{\alpha}\right)^{\beta-1} e^{-(t/\alpha)^{\beta}} \tag{5}$$

In this equation, α is the scale parameter that represents the characteristic life or mean life where 63.2 % of the population is expected to fail. A higher α value typically means a longer expected lifetime, and β is the shape parameter, which determines the behavior of the failure rate. If $\beta < 1$, the failure rate decreases over time, indicating early-life failures. If $\beta = 1$, the failure rate remains constant, which corresponds to the exponential distribution. If $\beta > 1$, the failure rate increases over time, indicating wear-out failures. In the context of the lifetime distribution, β provides insight into the variability of lifetimes. A higher β value suggests less variability, meaning lifetimes are more tightly clustered around the mean, while a lower β indicates greater variability, with a broader spread of lifetimes.

The cumulative distribution function (CDF) or unreliability function, which gives the probability that the time to failure is less than or equal to t, is given by 6:

$$F(t) = 1 - e^{-(t/\alpha)^{\beta}} \tag{6}$$

From the CDF, the reliability function $R(t)$ can be derived by 7, representing the probability that a component will operate without failure up to time t:

$$R(t) = e^{-(t/\alpha)^{\beta}} \tag{7}$$

So in this study, 10, 000 simulations are carried out via the Monte Carlo method [23] to construct the end-of-life probability distribution function. These findings indicate that the lifetime of these sets is distributed according to the Weibull distribution, which will be shown in the next section. As well, the CDF of the devices will be extracted. The assumptions and equations introduced in this section will be applied in the subsequent analysis to incorporate both individual and combined parameter uncertainties.

B. MONTE CARLO-BASED ANALYSIS OF PARAMETER UNCERTAINTIES IN POWER DEVICE RELIABILITY

As mentioned in the previous part, in actual field operations, the time to end-of-life of power devices can vary due to tolerances in physical parameters and differences in experienced stresses. So, in this section, uncertainties are considered by using Monte Carlo simulations and analyzed to assess the reliability of the device and to evaluate their impact on the lifetime estimation of power devices. This approach involves plotting the distributions of temperature-related lifetime constants β_1 and β_2, along with other parameters of the lifetime model β_3-β_6. As well, different values of $V_{ce,on}$ lead to different thermal stresses, impacting parameters such as T_{jmin} and ΔT_j.

To capture this inherent variability in the lifetime model parameters, each parameter is modeled as a normally distributed variable. This choice is motivated by the assumption that the deviations in parameters due to manufacturing tolerances, measurement errors, or environmental fluctuations are symmetric and centered around a nominal value. Each parameter's nominal value (μ) is used as the mean of the normal distribution, while the standard deviation (σ) is defined as a fixed fraction of the absolute value of the nominal value. In this study, firstly, two uncertainty margins are considered (5 % and 10 %). The probability density function (PDF) for a normally distributed parameter x is given by (8):

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \tag{8}$$

This function describes the likelihood of different parameter values occurring. A larger σ results in a wider distribution, indicating more variability and uncertainty in that parameter.

Figure 1 illustrates the PDFs for each parameter under both uncertainty levels. As shown, increasing the uncertainty margin leads to a broader spread in the distribution.

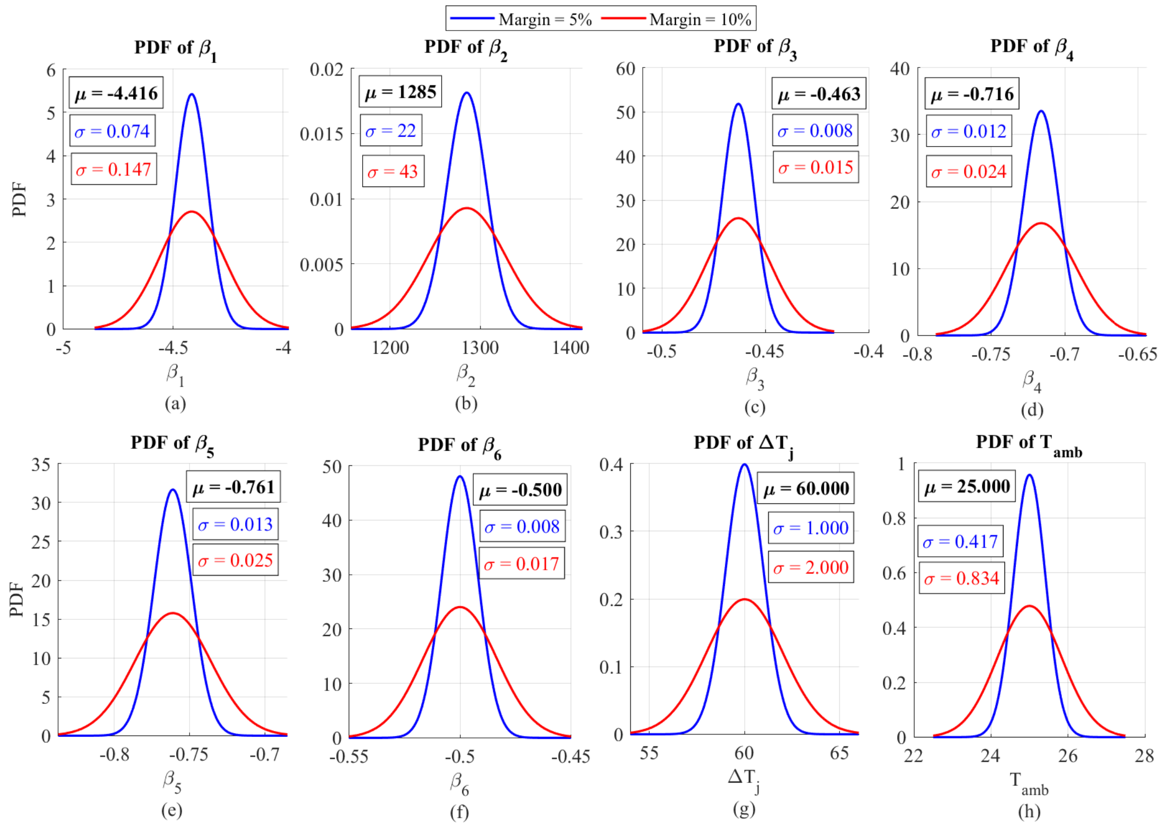

FIGURE 1. **Normal Probability Density Functions (PDFs) of Lifetime Model Parameters.**

These distributions serve as the basis for the Monte Carlo simulations, ensuring that parameter variability is statistically incorporated into the reliability analysis.

So the sensitivity of the end of life of the device to β_1-β_6, T_{jmin}, and ΔT_j can be evaluated individually or collectively in this section. Finally, the distribution of the end-of-life of IGBT can be determined, enabling a comprehensive lifetime analysis with a given degree of confidence.

1) SINGLE PARAMETER CHANGES

In this part, single parameters of the lifetime model are changed while keeping the other parameters at their constant values to conduct a sensitivity analysis. The parameters considered include the minimum junction temperature ($T_{j\min}$), the junction temperature swings (ΔT_j), and the fixed coefficients of the CIPS lifetime model (β_1-β_6). Thus, this analysis investigates the effect of parameter variations on the lifetime of power devices by incrementally adding margins to each parameter. Each case's lifetime distributions are derived using the Weibull function, which was shown in (5). Most studies commonly consider 5 % or 10 % parameter margins as a standard for accounting for uncertainties, often without further investigation into these margins [11], [24], [25], [26], [27]. Therefore, this study first examines both 5 % and 10 % margins, then extends the analysis to margins from 1 % to 13 % to evaluate their specific impact on the lifetime model to identify and select reasonable margins for lifetime estimation. The lifetime distributions were extracted under conditions when the ΔT_j and $T_{j,\min}$ are set to 60° C, and 25° C, respectively, based on the studied application, using assumptions and equations (2), (3), (4) and (5) in section II.(A). The results are presented in Figure. 2.

Figure. 2 illustrates Weibull distributions of IGBT lifetime under two different margin scenarios (5 % and 10 %) for lifetime model parameters (β_1, β_2, β_3, β_4, β_5, β_6, T_{amb}, and ΔT_j). The behavior of the Weibull parameters α (scale parameter) and β (shape factor) varies across parameters as the margins increase, reflecting the sensitivity of lifetime predictions to uncertainties in these parameters. As shown in this Figure, by increasing the margin from 5 % to 10 % for β_1, the characteristic lifetime (α) greatly increases (16.3 %), indicating a longer mean or characteristic life. However, such a substantial increase appears undesirable, as it reflects an excessive influence of β_1 uncertainty on the outcome. Also β, drops from 3.29 to 1.68, implying a great increase in variability and reduced predictability, which is problematic for reliability. For β_2, the increase in α is marginal (3.6 %), suggesting a reasonable response to increased margins and β, drops from 13.65 to 6.93. So, while α is stable, the β values vary visibly. Changes in β_3 result in relatively stable α values, while β decreases considerably, pointing to increased variability without much

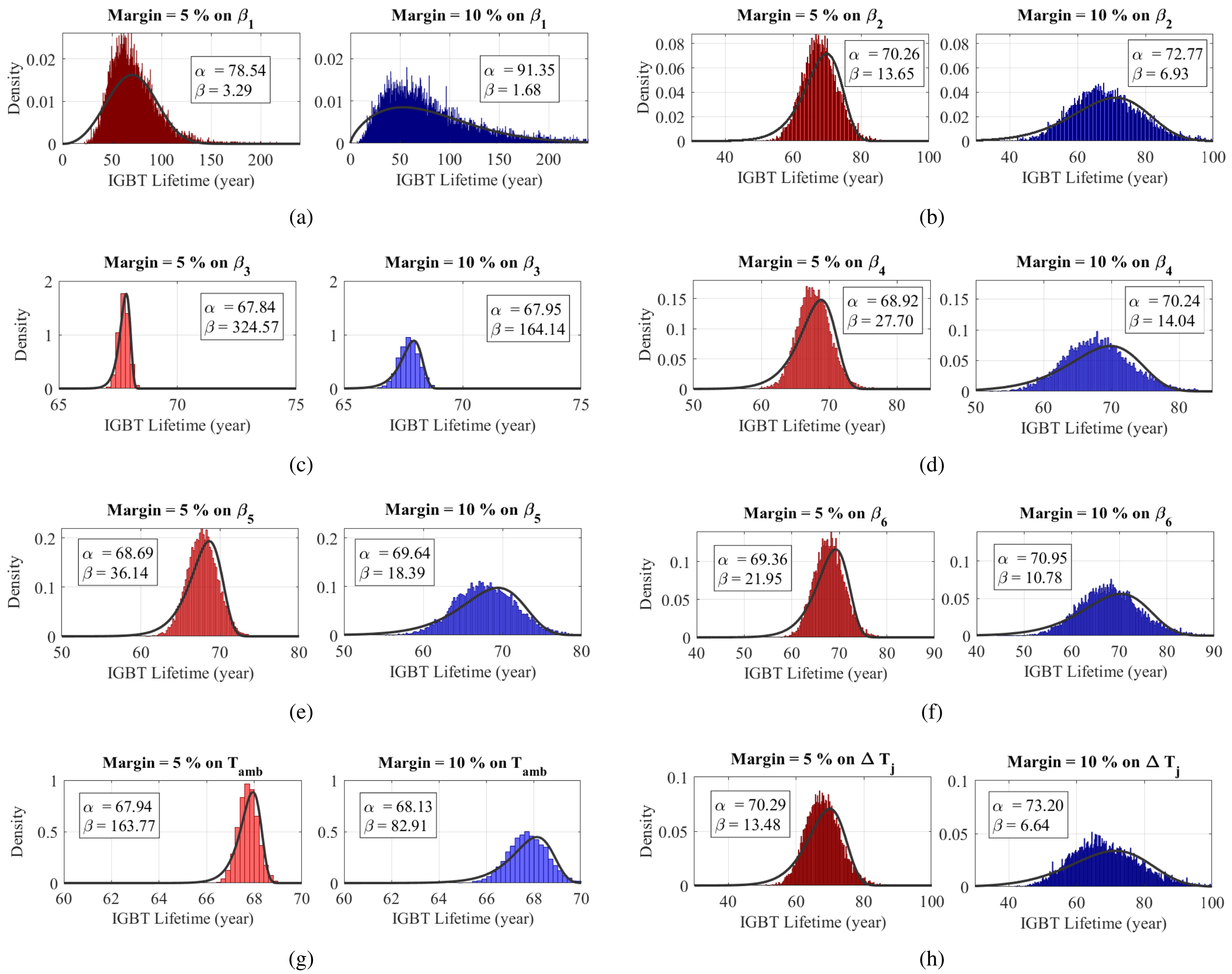

FIGURE 2. Weibull distributions and Montecarlo simulations with parameter variation.

change in the expected lifetime. However, both β values are unusually high, indicating extreme clustering of failure times. Similarly, increases in margins for β_4, β_5, and β_6 show slight increases in α, reflecting reasonable sensitivity to parameter variations. However, the noticeable drop in β suggests that the model is overestimating its sensitivity to the variability in that parameter. It shows that while the changes in α remain within acceptable bounds, the large drop in β raises concerns about an amplified response to parameter uncertainty. The changes in α for T_{amb} remain relatively stable, which is acceptable, while β visibly decreasing, pointing to an increased spread or more variability in lifetimes due to the uncertainty in T_{amb} which raises concerns regarding the robustness of the lifetime predictions. This indicates a possible overestimation of the impact of T_{amb} uncertainty by the model. On the other hand, the β values at both margins are extremely high, which is not practically reasonable. Such values indicate very sharp failure points or suggest that failures occur almost simultaneously. The α values increase slightly as the ΔT_j margins grow, while β decreases, indicating greater variability in the lifetime distribution. This broadening reflects increased uncertainty, as wider junction temperature swings directly contribute to thermo-mechanical stresses, which are critical in lifetime prediction models. Therefore, a reduction in β is, to some extent, justifiable. However, in systems with effective thermal management and stable operating conditions, a drop of this magnitude in β raises concerns about a potential overestimation of the impact of ΔT_j variability.

So in summary:

- β_1 and ΔT_j are highly sensitive parameters, as variations in both significantly affect α (scale parameter) and β (shape factor), highlighting their dominant influence on lifetime predictions. This is also physically relevant because ΔT_j is a key factor in wear-out mechanisms, and β_1 relates to the impact of ΔT_j on lifetime. Therefore, these parameters require careful control and precise estimation to avoid unrealistic predictions.

- Changes in α are reasonable for most parameters, except for the increases observed for β_1 when the margin shifts from 5 % to 10 %. However, the pronounced increases in α for β_1 point to an over-sensitivity to parameter variations, potentially reducing the reliability of the model's lifetime predictions.
- While α remains stable for β_3 and T_{amb}, the high β values are unlikely to be physically meaningful for reliability modeling. As they fail to represent realistic variability in practical systems. Additionally, the considerable reductions in β observed for parameters such as β_2, β_3, β_4, β_5, β_6, T_{amb}, and ΔT_j suggest an overestimation of the impact of parameter uncertainties on lifetime predictions. Moderate drops in β are reasonable for parameters with expected variability. However, large reductions in β can exaggerate the influence of these uncertainties, particularly in well-controlled environments.

This analysis emphasizes how crucial it is to understand and regulate uncertainty in these crucial elements in order to obtain precise power device lifetime estimates. The CDF (Cumulative Distribution Function) of the devices for each parameter variation of 5 % and 10 % is shown in Figure. 3 to validate the results presented in Figure. 2. Additionally, the B_{10} lifetime of the device, which indicates the time at which 10 % of devices will fail, is analyzed. Notably, according to this figure, when the parameter β_1 varies from 5 % to 10 %, the B_{10} life reduces noticeably from 40 to 23.5 years. Despite α being smaller at the 5 % margin compared to the 10 % margin case, its B_{10} life is higher because its β is larger, meaning failures are more concentrated later, and failures during the initial years are less common. Similarly, for variations in ΔT_j, the B_{10} life shows a considerable reduction from 59.6 to 51.8 years. So, these show the dominant influence of these two parameters in lifetime estimation. In contrast, variations in other parameters result in only minor changes in the B_{10} life. Therefore, the impact of these parameter uncertainties on lifetime appears to be negligible. Also, the B_{10} lifetime of the device under different uncertainties for various parameters was relatively similar or close, except for β_1, where it was lower, ranging between 23 and 40 years. This highlights the remarkable impact of β_1 on the device's lifetime. These findings corroborate the results and discussions presented in Figure. 2.

To gain clear insights into how parameter variations impact lifetime estimation and to analyze the sensitivity of these parameters, the correlation between parameter changes and their corresponding Weibull parameters was investigated across different junction temperature swings (ΔT_j). This sensitivity analysis considered variations ranging from 1 % to 13 % for each single parameter. The results of these investigations provide a detailed examination of parameter uncertainties on the lifetime estimation. This analysis is shown in Figure. 4, provides several important insights into the sensitivity of each parameter to uncertainty and their impact on lifetime predictions.

Firstly, variations in the Weibull distribution parameters, α and β, as a function of margin, are largely independent of the junction temperature fluctuations (ΔT_j). This suggests that changes in margins affect the lifetime parameters consistently across different temperatures, providing similar results that are largely invariant to thermal conditions.

Secondly, for all parameters examined, the variation in the shape parameter (β) is more pronounced than that of the scale parameter (α) at lower margins. This indicates that the spread in lifetime, represented by β, is more sensitive to small changes in margin than the average or characteristic lifetime (α). However, as the margin increases beyond about 5 %, the changes in β become smaller compared to those at lower margins. This behavior highlights that margins below 5 % can noticeably impact variability, which challenges their applicability in practical scenarios.

Moreover, according to these results, the parameters β_1 and ΔT_j emerge as highly sensitive, with changes observed in both α and β. For β_1, α increases continuously with increasing margins. At higher margins, the increase becomes significant, which questions the practicality of such scenarios. Additionally, β experiences a steep decline, particularly for margins below about 5 %, further emphasizing the sensitivity of this parameter. Similarly, margins in ΔT_j shows a slight but consistent increase in α with increasing margins, reflecting its contribution to lifetime predictions in a reasonable manner. However, a sharp decrease in β, particularly for margins below about 5 %, highlights its dominant role in introducing variability. These results underscore the importance of precise margin assumptions for these parameters to avoid overestimating variability and to ensure reliable predictions. For the parameters β_2, β_3, β_4, β_5, β_6, and T_{amb} variations, similar trends are observed. The scale parameter α remains relatively stable or shows slight changes, while β exhibits noticeable declines, especially at smaller margins. These declines suggest that the model is overly sensitive to variations in these parameters. On the other hand, the β values at lower margins are very high for these parameters, suggesting extremely narrow lifetime distributions or nearly deterministic failures, which are unrealistic in practical applications.

Based on these findings, a 5 % uncertainty margin is recommended for highly sensitive parameters as a balanced trade-off—it captures the essential parameter variability and avoids unrealistic lifetime predictions.

Moreover, uncertainties in other parameters (β_2 to β_6 and T_{amb}) can be considered negligible for lifetime estimation, as their associated β values remain high even at lower margins, and their B_{10} lifetime shows minimal variation according to the results presented in Figure 3.

To quantitatively justify the choice of a 5 % uncertainty margin, the coefficient of variation (CV) was calculated for the predicted lifetime distribution at each margin. CV measures the relative variability of lifetime estimates by normalizing the standard deviation to the mean, providing an indication of how prediction uncertainty increases with

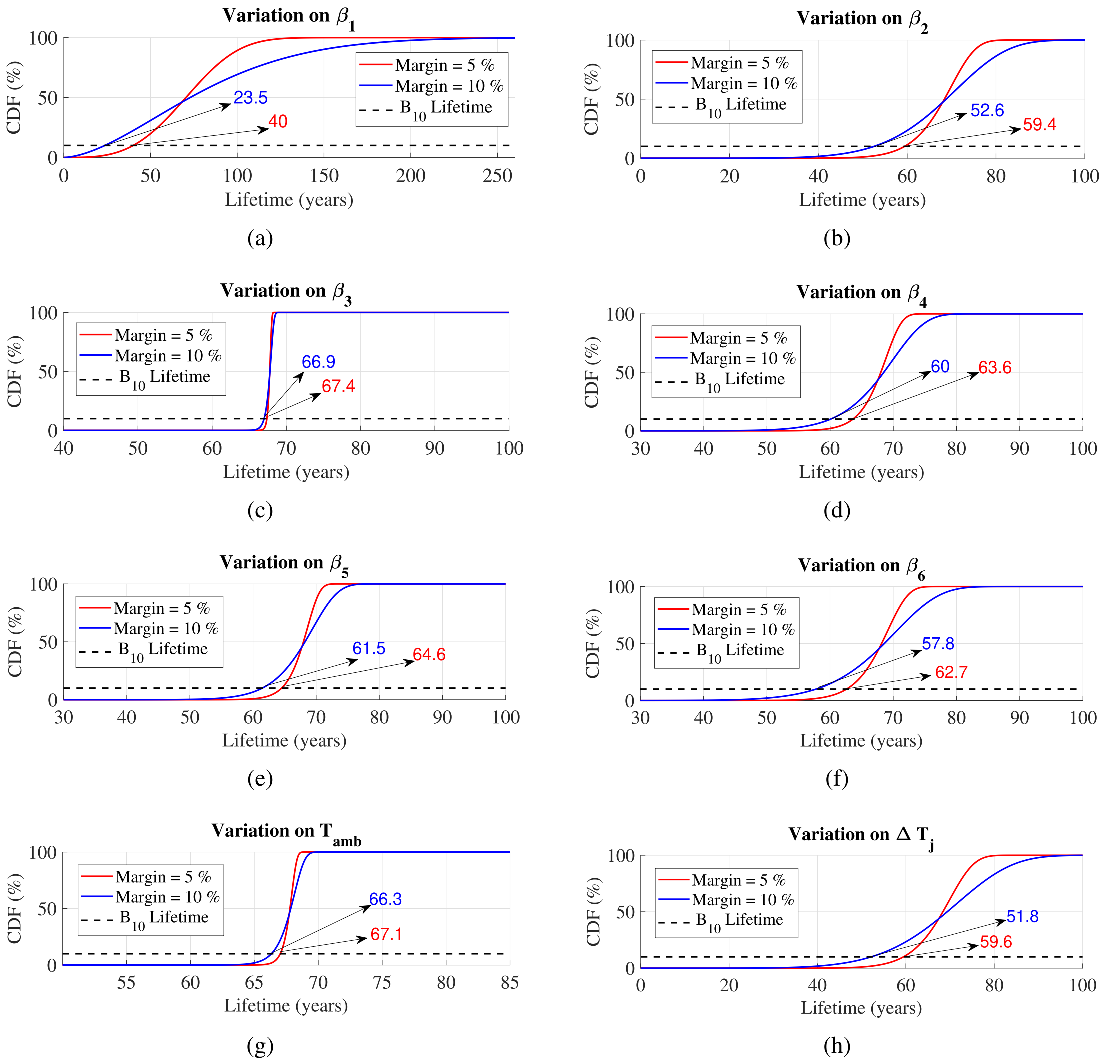

FIGURE 3. CDF or unreliability function of the devices, considering each parameter variation.

parameter uncertainty. The CV was calculated as 9:

$$CV = \frac{\sigma}{\mu} \times 100 \tag{9}$$

where σ is the standard deviation and μ is the mean of the predicted lifetime distribution. In reliability analysis, a higher CV indicates greater unpredictability in lifetime estimation, which may compromise design robustness. The CV of lifetime was calculated for each parameter across uncertainty margins in Fig. 5. As shown in this Figure, β_1 exhibits the highest sensitivity to parameter uncertainty, with CV increasing from approximately 6 % at 1 % margin to 30 % at 5 % margin, and continuing to rise beyond this point while other parameters remain in lower CV even at 13 % margin. Therefore, selecting a 5 % uncertainty margin represents a reasonable balance: it accounts for parameter variability while maintaining an acceptable level of predictive confidence, before prediction uncertainty becomes excessively large.

In addition to the coefficient of variation analysis, the α-β plots for each parameter's uncertainty were investigated to further justify the suggesting of a 5 % margin which are shown in Figure. 6. Three key observations were made from the plots:

- **Stabilization of β beyond 5 %:** Across all parameters, the shape parameter β exhibits a sharp decline as the uncertainty margin increases up to about 5 %. However, beyond this point, the β values tend to flatten. This indicates that further increases in uncertainty margin result in only marginal changes in β, implying a reduced effect on predictability.
- **High β values below 5 %:** As seen in subplots (b) through (h), the β values are excessively high, especially at margins below 5 %—often exceeding 10. In practical reliability assessments, such high β values correspond to unrealistically low variability, which may lead to overconfident and potentially misleading lifetime predictions.

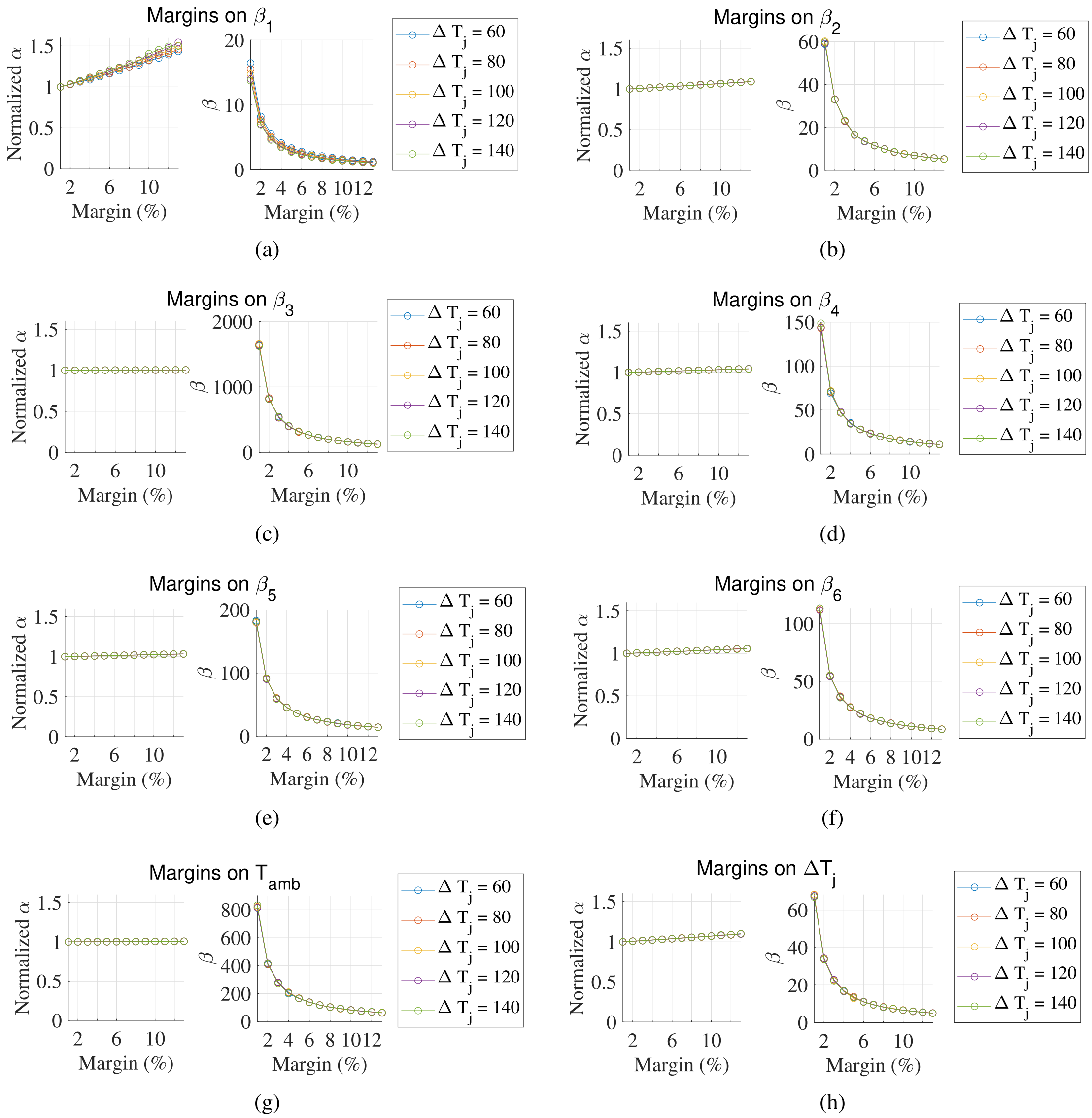

FIGURE 4. Correlation of each parameter with the margin percentage on the Weibull parameters (α and β).

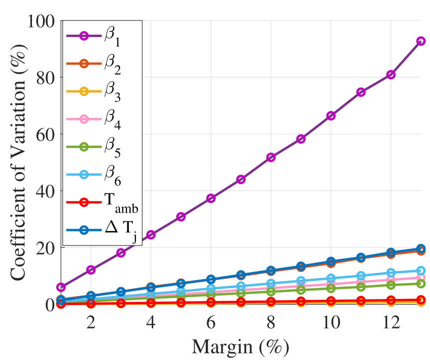

FIGURE 5. Coefficient of variation (CV) of the predicted lifetime versus uncertainty margin for each model parameter.

- **Growth in α for β_1 uncertainty:** In the case of β_1 uncertainty (subplot (a)), the scale parameter (α) increases sharply beyond the 5 % margin. These changes are disproportionately large and not physically justifiable within a realistic reliability estimation framework. In contrast, by increasing margins for other parameters, the increase in α remains below 10 %, suggesting more acceptable lifetime shifts.

In conclusion, a 5 % margin suggests achieving the most reasonable lifetime estimates, as it effectively balances the spread (β) without significantly altering the mean lifetime (α). This analysis underscores that β_1 is a dominant factor in reliability modeling and must be carefully considered to maintain realistic predictions, as uncertainties in it significantly influence both the expected lifetime and its variability.

2) VARIATIONS ACROSS ALL PARAMETERS

The second part of this study delves into the analysis of the combined effects arising from simultaneous variations

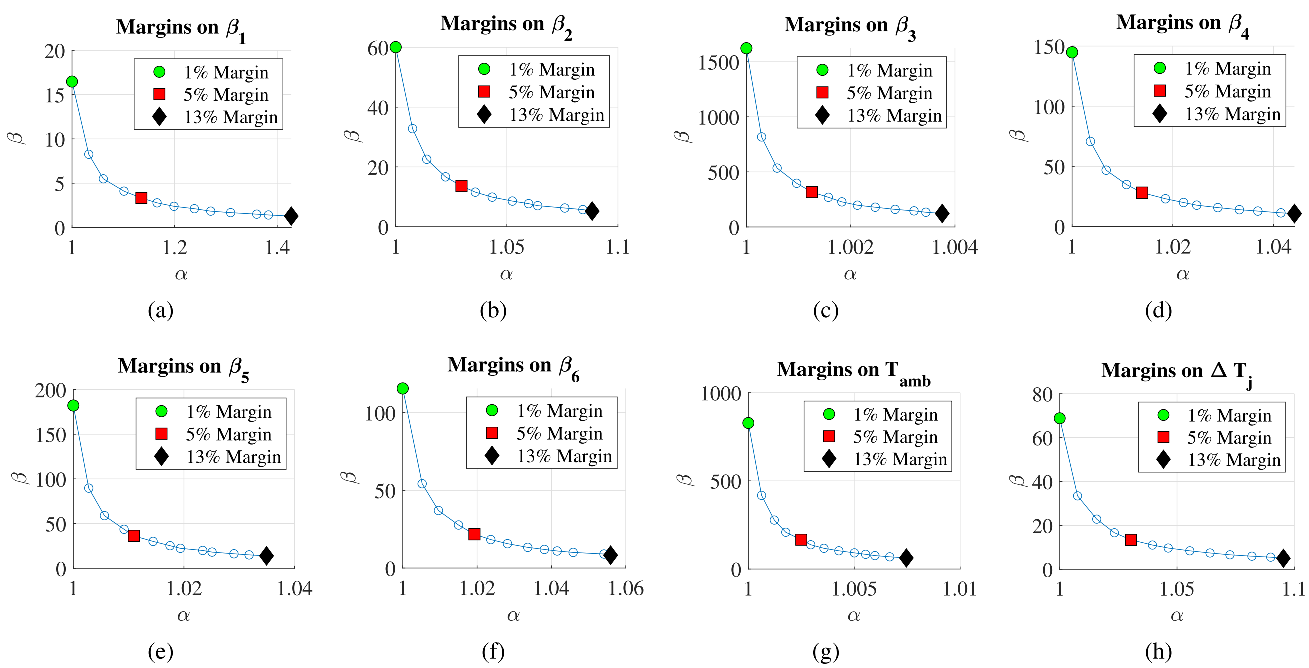

FIGURE 6. Weibull scale (α) versus shape (β) parameter plots for different model parameters under varying uncertainty margins (1 %-13 %).

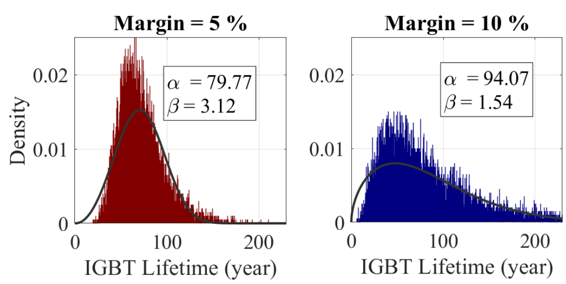

FIGURE 7. Weibull distributions and Montecarlo simulations by considering all parameters variations together.

in all parameters. Specifically, it examines concurrently the impact of introducing 5 % and 10 % variations across all parameters. The results of this approach are then compared to the previous section, where only individual parameters were varied. By contrasting these two scenarios, we gain deeper insights into how uncertainties collectively influence the lifetime estimation of power devices. To quantify these effects, the lifetime distributions are derived using Weibull distributions and Monte Carlo simulations for each margin under the same conditions as in the previous section (ΔT_j and $T_{j,\min}$ are set to 60° C, and 25° C, respectively). The results of this analysis are presented in Figure. 7.

According to Figure. 7, the following observations is extracted when all parameters are varied simultaneously:

- **5 % Margin:** The values of $\alpha = 79.77$ and $\beta = 3.12$ indicate a longer expected lifetime. The β value suggests that the lifetime distribution is at an acceptable level.
- **10 % Margin:** With $\alpha = 94.07$ and $\beta = 1.54$, there is a noticeable increase in the characteristic lifetime. However, the significant decrease in β indicates much greater variability, leading to a broader distribution of lifetimes. This suggests that while the average lifetime can be longer, there is less predictability, and some devices could have significantly shorter or longer lifetimes than expected. Such broad variability in lifetimes is undesirable for critical applications like EV chargers, where consistent performance is crucial.

Overall, a 5 % margin is suggested as ideal for achieving a balanced trade-off between expected lifetime and variability, based on the above observations. Moreover, this section provides further support for the recommendation of the 5 % margin given in the previous section.

By comparing the results of this part (Figure. 7) and the previous section (Figure. 2), it is evident that the changes in α and β for the combined parameter variation closely resemble those observed for the β_1 parameter variation in Figure. 2, indicating that β_1 has a more significant impact on lifetime predictions compared to other parameters. Specifically, varying only β_1 and increasing the margin from 5 % to 10 % leads to a substantial rise in α and a marked decrease in β, ($\alpha = 78.54$ to $\alpha = 91.35$ and $\beta = 3.29$ to $\beta = 1.68$). This trend is mirrored in the combined parameter variation, where α increases from 79.77 to 94.7 and β decreases from 3.12 to 1.54. This similarity suggests that β_1 exerts a dominant influence on the overall lifetime predictions when margins are varied. Consequently, selecting appropriate β_1 should be prioritized in lifetime models for more realistic predictions.

The CDF function of the devices, considering all parameter variations with margins of 5 % and 10 %, is shown in Figure. 8 to validate the results presented in Figure. 7. Additionally, the B_{10} lifetime of the device is illustrated.

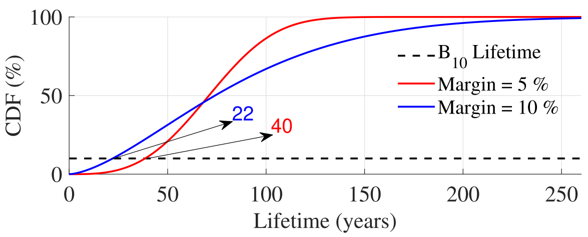

FIGURE 8. CDF or unreliability function of the devices, considering all parameter variation.

According to Figure. 8, when the parameter variations increase from 5 % to 10 %, the B_{10} lifetime experiences a substantial reduction, from 40 to 22 years. This result closely aligns with those presented in the Figure. 3(a), where the variation of only the β_1 parameter was considered. This strong correlation underscores the critical influence that β_1 exerts on the overall lifetime estimation, highlighting its importance in reasonably predicting the device's reliability under varying conditions. In conclusion, based on investigations in the previous section and this section, it is reasonable to suggest uncertainties in β_1 and ΔT_j while potentially ignoring other parameters, provided that the contribution of those parameters is negligible or predictable. These two parameters have demonstrated a dominant influence on lifetime predictions, particularly affecting both the characteristic lifetime (α) and variability (β). By focusing on these critical parameters, the reliability estimation can be simplified, ensuring practical and realistic lifetime estimations, which is expected physically as β_1 is the factor of ΔT_j, impacting the lifetime of the device under wear-out failures. Similar to the previous part, the 5 % margin suggests a trade-off between predictability and expected lifetime and supports the prior recommendation.

III. CONCLUSION

This study provides a comprehensive analysis of the impact of parameter uncertainties on the lifetime prediction of power devices. By employing an empirical corrected CIPS lifetime model alongside Monte Carlo simulations, the research examined both individual and combined effects of parameter variations on the predicted lifetime.

The single parameter changes analysis showed that the Weibull distribution parameters are highly dependent on changes in parameters like minimum junction temperature, junction temperature swings, and lifetime model constants like (β_1 to β_6), especially β_1. These variations have a significant impact on the shape parameter (β) and scale parameter (α) of the Weibull distribution, which in turn affect the expected lifetime and its variability.

This study uniquely contributes to the field by addressing the lack of justification for commonly assumed parameter uncertainty margins in existing research. By systematically analyzing the impact of these margins on lifetime predictions. The study suggests a balanced and physically reasonable assumption of a 5 % margin for key parameters. This approach not only provides a rationale for margin selection, but also enhances the robustness and reliability of lifetime modeling, offering valuable insights for the design and assessment of power devices. It was clear from the analysis of simultaneous parameter variations that the changes in α and β for the combined parameter variation closely resembled those observed for the β_1 single parameter variation. It highlights the dominant influence of the β_1 parameter on overall lifetime predictions. In summary, the findings suggest that it is reasonable to focus on uncertainties in β_1, while disregarding other parameters whose contributions are negligible. Concentrating on this critical parameter enables a simplified reliability model that contributes to practical lifetime predictions.

The study's findings emphasize how important it is to consider parameter uncertainties when analyzing the reliability of power devices. It is essential to select these uncertainties carefully, especially in parameter like β_1.

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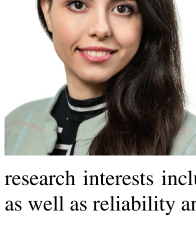

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