ABSTRACT

Title of Thesis: UTILIZATION OF DATA AND MODELS

FOR COMMERCIAL OFF THE SHELF (COTS) ELECTRONIC COMPONENT SELECTION AND RELIABILITY

ASSESSMENT

Edmond Elburn, Master of Science, 2018

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The continued growth of commercial off-the-shelf (COTS) parts in electronic systems

and hesitance of use in some applications necessitates the development of methods to

evaluate part reliability. An information-based reliability evaluation method has been

developed based on failure mechanism models incorporating application conditions

and part parameters. The sources of the information necessary for COTS parts were

identified along with the information these sources provide. The sources were

contrasted with the information required for military, space, or automotive grade parts.

Multiple methods of approximating the application conditions and part parameters

were developed and incorporated into the reliability methodology along with the

impacts of uncertainty levels on the reliability prediction. An evaluation of information

availability was completed, and metrics were developed to quantify the thermal and

material information provided for parts. An analysis of 22 COTS parts evaluated the

metrics' effectiveness, and reliability estimations compared the changes in part

parameters and conditions.

UTILIZATION OF DATA AND MODELS FOR COMMERCIAL OFF THE SHELF (COTS) ELECTRONIC COMPONENT SELECTION AND RELIABILITY ASSESSMENT

by

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List of Abbreviations and Acronyms

CAS Chemical Abstracts Service

COTS Commercial off the Shelf

FMMEA Failure Mode, Mechanism, and Effect Analysis

IGBT Insulated Gage Bipolar Transistor

MIA Material Information Availability

MOSFET Metal Oxide Semiconductor Field Effect Transistor

MSL Moisture Sensitivity Level

PPAP Production Part Approval Process

TIA Thermal Information Availability

QML Qualified Manufacturer List

QPL Qualified Products List

Chapter 1: Introduction

Almost every engineered system and piece of technology in the world today utilizes, is managed by, or is controlled using an electronic system. Each electronic system contains individual parts that have specific functionality. As electronic systems continue to grow and expand into new areas and aspects of life, ensuring proper performance and reliability continually becomes more important and crucial.

Electronic parts and systems have been used for many years in commercial, industrial, military, medical, aerospace and many other applications. Each of these applications has specific requirements and factors that distinguish it from others such as environmental conditions, reliability requirements, and design time. Historically, different grades of parts have been developed and qualified by part manufacturers for specific application, such as space, automotive, or military grade parts. With the continued growth of commercial applications and reduction in availability of "higher" grade application parts, the use of commercial off the shelf (COTS) parts are a likely source going forward to fill the need for military, space, and other users.

There is no single accepted definition for COTS devices. Each organization, manufacturer, or person has their own interpretation of the acronym that is different. Frequently, the differences are based off the intended application or use. Table 1 lists some different definitions provided for commercial off the shelf parts, systems, software, or designs.

Table 1:Definitions of COTS collected from various sources

Organization / Person	Definition
Fairchild Defense [1]	"If you can buy it from a catalog without modification it is COTS"
Society of Automotive Engineers (SAE) / NASA Jet Propulsion Lab (JPL) [2]	"An electronic component developed by a supplier for multiple customers, whose design and configuration are controlled by the supplier's or an industry specification."
Federal Acquisition Regulation (FAR) [3]	A commercial item sold in substantial quantities in the commercial marketplace; and offered to the government, under a contract or subcontract at any tier, without modification, in the same form in which it is sold in the commercial marketplace.
COTS Journal [4]	"COTS is generally defined for technology, goods and services as: a) using commercial business practices and specifications, b) not developed under government funding, c) offered for sale to the general market, d) still must meet the program ORD"
IEEE Requirements for Replacement Parts for Class 1E Equipment in Nuclear Power Generating Stations [5]	Not subject to design or specification requirements that are unique to nuclear power plants, used in applications other than nuclear power plants, and ordered from the manufacturer/supplier on the basis of specifications set forth in the manufacturer's published product description (for example, a catalog).
ISO/IEC/IEEE Systems and software engineering Content of life-cycle information products [6]	"Product available for purchase and use without the need to conduct development activities."
UMD: Center for Public Policy and Private Enterprise [7]	"Software or hardware that is commercially made and available for sale, lease, or license to the general public and that requires little or no unique government modifications to meet the needs of the procuring agency."
NASA [8]	"Any grade [component] that is not space qualified and radiation hardened."

Based off the definitions from various sources, COTS devices are defined as parts developed for multiple customers where design and specifications (testing, ratings, documentation, process change policies) are established and controlled solely by the part manufacturer. The part manufacturer will select the part specifications

without specific input from an end user and the part is not qualified for a specific application.

There are two major categories of parts that do not fall within the definition for COTS devices. Parts that have been qualified for military, space, or automotive standards specifically are not considered COTS parts. Additionally, "custom" parts that are specifically designed for a unique customer are also not COTS devices. There are unique situations that blur the lines between these like "enhanced" products provided by part manufacturers that are commercially available, designed for military or aerospace applications, but do not meet all of the qualification requirements of QML devices [9], [10].

The motivation for using COTS devices in higher grade applications has been attributed to many factors [11]. The increased demand of commercial applications has resulted in COTS devices having the most advanced technologies and largest scale of production. Alongside the increase in commercial parts has been a decrease in military and space parts due to the small number of purchases and more demanding and complex design considerations. COTS parts are available for a lower cost than military or space grade parts on a per unit basis. COTS parts are provided through more distributors resulting in better availability and flexibility for users. COTS parts have better process control due to the higher production scale.

The newest technological parts are primarily released COTS versions. For example, Texas Instruments released 151 COTS parts between March and September of 2018, compared with only one space or military qualified part during that same

period of time (see Table 2 for detailed overview) [12]. Texas Instruments is known as one of the largest semiconductor part manufacturers and has provided military and space qualified parts for over 60 years [13]. Analog devices, who also provide military and space qualified parts, has only released one new aerospace part design in the last 6 months compared with 46 new COTS parts [14].

Table 2: New parts released by Texas Instruments (March – September 2018) [12].

Part Rating (By Texas Instruments)	COTS	Automotive	Hi-Reliability (COTS+)	Space / Military
Amplifiers	22	7	0	0
Audio	5	2	0	0
Clock and Timing	3	0	0	0
DLP Chipsets	0	1	0	0
Data Converters	12	1	0	1
Interface	29	1	0	0
Isolation	1	0	0	0
Logic	2	1	0	0
Microcontrollers	9	0	0	0
Motor Drivers	5	1	0	0
Power Management	47	12	0	0
Processors	2	0	0	0
RF and Microwave	2	0	0	0
Sensors	9	0	0	0
Switches and Multiplexers	3	0	0	0
Total	151	26	0	1

Another assumption is that COTS parts are more readily available and at a lower cost than equivalent non-COTS parts. This was evaluated by comparing similar parts of different part types (COTS vs non-COTS) and evaluating the cost and availability. Three comparisons have been made based off parts with different ratings but the same functionality (summary of results in Table 3). The non-COTS parts are on average over 5x more expensive than the equivalent COTS parts. Additionally, the COTS parts had

over 10x more availability from multiple distributors, whereas the non-COTS were only available from a single overstock distributor.

Table 3: Comparison of different part type costs and availability

Part Category	Part Rating	Unit Cost / 100 Units	Total Inventory	Min Order Quantity	Authorized Distributors
Differential	COTS	\$2.05	> 5,000	n/a	3
Comparator	Military	\$21.16	537	n/a	1 (Overstock)
PWM	COTS	32.16	1,000 - 5,000	1	3
Controller	Space	433.97	35	20	1 (Overstock)
BJT	COTS	4.31	> 40,000	5	4
Transistor	Space	15.15	0	100	1

There had been an assumption that military or space grade parts (non-COTS) are reliable in demanding applications [15], but this does not exist for COTS parts. This assumed reliability comes from decades of use and standardized qualification and screening processes that are completed before and while the part is in use. Due to COTS devices not having the same standardized qualification process, there has been hesitation towards use. Thus, a s additional tests are completed by users to ensure that COTS can meet the needed reliability for space or military applications [16]. This reduces the cost benefit associated with using COTS part in military or space applications [17]. The additional evaluation period and testing has made it difficult to use COTS devices in higher grade applications and necessitates the development of new reliability estimation methods. Additionally, there is an assumption that the information provided by non-COTS parts is more detailed, of higher quality, and more readily available than for COTS parts.

Space applications have high reliability expectations due to long mission times and required functionality in a single instance. Additionally, the increased risk of radiation-based failure mechanisms means that the reliability evaluation of parts for space applications is completed rigorously and historically only space qualified parts have been used. COTS parts do not complete the additional qualification testing associated with radiation failure mechanisms. Various articles have evaluated the reliability of COTS parts in space applications by determining the susceptibility of COTS parts to radiation through physical and simulated testing [17]–[20].

A subset of space programs and applications are non-safety critical such as CubeSat. These missions operate on lower budgets and can utilize the more advanced technology and lower cost benefits of COTS parts. Numerous project reports have been documented based on the process used to implement COTS parts into space applications and what challenged and observations were found [2], [11], [16], [21]–[24]. NASA has used COTS parts in aerospace applications in specific instances. NASA balances the criticality and severity of the mission as well as the expected lifetime requirements when determining whether to use COTS parts or not. NASA traditionally completed an up-screening process when qualifying a COTS part for a specific space applications including satellite and rover systems [8]. Depending on the criticality of the mission and the environmental conditions the part will be used in, additional testing, fault tolerant designs, and / or radiation hardening may be required [8].

In addition to reliability concerns, less information is historically assumed to be available for COTS devices compared with aerospace and military grade devices [2]. Due to the standardized development process and long-term usage, military and space grade parts have historical usage data, lessons learned from previous part iterations, and have been evaluated for specific failure mechanisms like radiation impact that COTS devices have not been. This perceived lack of information has made it difficult for military and space customers to consider COTS devices without a detailed analysis to ensure proper performance.

An information-based reliability assessment is utilized to evaluate the reliability of COTS devices in space or military applications and incorporates the information that can be found for the part. This will be completed using physics of failure-based models that are dependent on part specific attributes, application conditions, and modeling constants. The implementation is based on Monte-Carlo sampling, meaning that each information input is considered a distribution and thus the resultant time to failure is a distribution which can be analyzed. A summary of the process is provided in Figure 1.

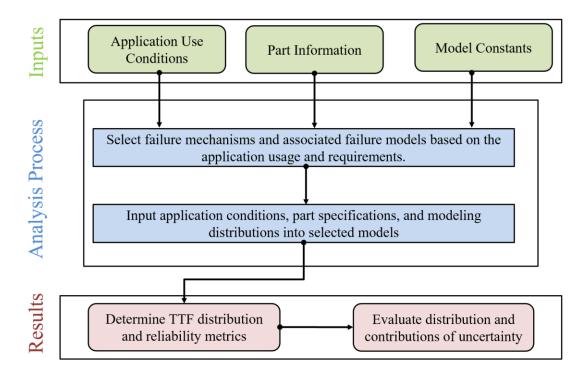


Figure 1: Process flowchart for estimating COTS part reliability using information

The outline of this thesis is as follows. First, the motivation for using reliability-science methodology is discussed in Chapter 2 and used to determine the information that must be found to estimate reliability. This chapter also includes a discussion and critique of the constant failure rate reliability methodology that is still used in industry to this day. Chapter 3 discusses information collection methods for the inputs needed for using the physics of failure methods, including an analysis of the information that is available for COTS and non-COTS devices. Chapter 4 defines information availability metrics based on thermal and material documentation for COTS devices and how to implement them in the time to failure estimation method, including a case study analysis with 22 COTS parts that are to be used in an aerospace application. Chapter 5 presents the time to failure estimation method and results comparing

different information sources and values. Finally, contributions and recommendations for future work are provided in Chapter 6.

Chapter 2: Evaluating Reliability of Electronic Parts

Reliability is the ability of a product to meet performance specifications without failure in for a certain length of time in specific application conditions [25]. The classical method of calculating reliability of a part or system assumes of a constant failure rate. The constant failure rate assumption implies that the rate of failures will not change over the part's entire lifetime. This assumption is known to be false.

The reliability of a part is determined based on many factors including the manufacturing quality, design, and application in which it is used. The life of a part is approximated using the bathtub curve (shown in Figure 2) which highlights three main regions based on the hazard rate: infant mortality, useful life, and wearout. The hazard rate is the probability of the first failure of a part. Infant mortality failures typically occur due to manufacturing defects. The useful life period is when the hazard rate is at its lowest and failures that occur during this period are typically random. The final stage is the wearout period. This region features an increasing failure rate over time as the device reaches the end of its designed life. The bathtub curve is an approximation and still does not account for all situations. For example, a part used in a high stress environment can lead to a wearout failure occurring early in the life.

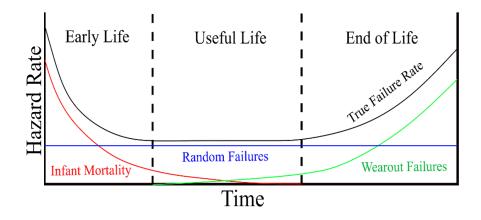


Figure 2: Bathtub curve for a part representing the hazard rate over time

The most common (constant) failure rate metric is the failures in time (FIT) rate. This value determines the number of parts that are expected to fail per billion hours of usage up to a certain confidence level. The method of determining the constant failure rate value is based on many assumptions that rarely hold and are not generalizable for different application conditions. Many manufacturers use JESD85 [26], a standard for determining FIT rates (failures per billion hours) which uses the following process:

- 1. Test parts in high stress environments that accelerate the rate of failures. The assumption is made that parts tested at high temperatures will still fail by the same method as if they were tested in a less stressful environment.
- 2. Apply the Arrhenius equation to determine the acceleration factor (AF) between the high-stress levels and an assumed normal condition (an activation energy level must also be assumed in this step). The Arrhenius equation (with a temperature dependency relationship) is provided in equation 1.

$$AF = \exp\left(-\frac{E_a}{k}\left(\frac{1}{T_1} - \frac{1}{T_2}\right)\right) \tag{1}$$

where AF is the acceleration factor, E_a is an assumed activation energy (most commonly selected as 0.7 eV), k is Boltzmann's constant, and T_1 / T_2 are accelerated and selected normal usage conditions.

3. Determine the equivalent device hours (EDH) by multiplying the acceleration factor by the total testing time in the accelerated state ($Time_{accel}$). This formula is shown in equation (2). The assumption is also made that the total acceleration time is the sum of all individual part times that have been tested in the stressed state.

$$EDH = (AF)(Time_{accel}) \tag{2}$$

4. Convert the number of failures with the chi-squared distribution using the number of samples and a selected confidence level (typically 60% or 90% for manufacturers). The assumption is made that failures occur immediately after testing is ended when using the chi-squared distribution.

$$M = \frac{\chi^2(\alpha, \nu)}{2} \tag{3}$$

where M is the projected number of failures following the chi-squared distribution with confidence level of α and $\nu = 2 * Failures + 2$.

5. Determine the failure rate (λ) by dividing the chi-squared value (M) by the equivalent part hours (and multiply by 10^9 if converting to FIT rate).

$$\lambda = \frac{M}{EDH} \tag{4}$$

$$FIT = \lambda * 10^9 \tag{5}$$

One key aspect to this process is the conversion from accelerated to normal conditions using the Arrhenius equation (and any assumed activation energy). The activation energy is process specific and cannot be generalized for entire families of parts. The activation energy for an electromigration related failure is not the same as the activation energy for a dielectric breakdown process and must be distinguished. The construction, design, material properties, manufacturing, and usage will all impact the mechanism of failure and change the activation energy.

Another important aspect to determining the constant failure rate is the projected number of failures using the chi-squared distribution. This methodology is used because in many cases there are no failures observed during the testing. How can an accurate failure rate be determined if there are no or very few observed failures in the testing? For example, a Texas Instruments reliability information table is provided in Figure 3 and shows that there were 0 failed parts out of the 24,231 samples that were each tested for 1000 hours at 125 °C. The MTBF (mean time between failures) and FIT rate are provided for the part based on the assumptions within the chi-squared distribution, confidence level, and application temperature.

	Early life failure rate	MIRE/FII		Early life failure rate supporting data		MTBF /	FIT sup	oporting data	a					
Part number	ELFR- DPPM	MTBF	FIT	Conf level (%)	Test temp (°C)	Sample size	Fails	Usage temp (°C)	Conf level (%)	Activation energy (eV)	Test temp (°C)	Test duration (hours)	Sample size	Fails
SN74AUP2G02DCUR	-	2.07x 10 ⁹	0.5	-	-	-	-	55	60.0	0.7	125	1000	24231	0

Figure 3: Sample Texas Instrument Part Reliability Information

Because a constant failure rate (and thus exponential failure distribution) is assumed, manufacturers can test many parts and convert it into an estimation on the failure rate for a single part number. The assumption is completed with the equivalent part hours conversion (step 3). Part manufacturers also complete this process for entire families of parts, even if this assumes that every part will have the same activation energy level and failure rate, which is not true. For example, ON Semi publishes the failure rate data for each of their families of parts, even if individual parts have a different design [27]. They even assume the same activation energy for all the different families of parts. An example document provided by ON Semi is shown in Figure 4. Vishay also provides reliability reports and the same failure rate values for part groups such as all N-channel MOSFETs [28]. These broad assumptions ignore the differences in designs, materials, and even technology levels, which would result in differences in dominant failure mechanisms. Because of these assumptions and lack of accounting for application conditions, it is not recommended to use failure rate data for projecting reliability metrics and instead consider potential failure mechanisms and associated models.





	Die Related Grand Summary Data								
		Activation Ever	0,	0.7 eV					
		Die Junction Temp		55°C					
	One-	Sided Upper Confid	dence Level	90%					
	Rejected			Equivalent Device-					
Technology	Devices	Sample Size	Device-Hours	Hours	FIT Rate				
ACMOS	0	14,376	5,353,408	499,521,307	4.61				
BP STD LINEAR	0	19,344	19,017,592	3,693,073,481	0.62				
BPT	2	4,864	3,723,552	1,093,334,401	4.87				
CMOS STD	0	13,024	5,656,320	1,118,469,126	2.06				
CMOS SUB	5	21,502	17,392,896	2,571,750,728	3.61				
HD3e	0	9,273	12,204,192	6,113,257,220	0.38				
HVFET	0	5,700	5,745,600	1,486,600,757	1.55				
I3T	0	1,391	1,442,448	356,072,711	6.47				
IGN IGBT	0	2,059	1,552,840	402,180,880	5.73				

Figure 4: Example constant failure rate information provided by part manufacturer (ON Semi) with listed assumptions on activation energy, confidence level, and application die junction temperature.

Only through determining the failure mechanisms for the part based off the type of usage and application conditions can the reliability be estimated, and appropriate risk mitigation performed. A failure mechanism is the physical, chemical, electrical, or other process by which a part fails and is fundamentally related to physical characteristics of the part [25]. Using failure mechanisms allows for a better representation of how the part can fail and thus better modeling method.

The reliability of a product is entirely dependent on the application and conditions in which the part is used. A COTS part that is reliable for a commercial application need not be considered reliable in a military or space application. To reduce

the need for qualification testing, an information-based reliability method is completed based on specific failure mechanisms associated with the part.

A failure mechanism is the root cause behind why the part has failed and is fundamentally related to the physical properties of the device [25]. In this thesis, dielevel semiconductor failure mechanisms and associated failure models are considered [29]. A failure model is connected with each failure mechanism to predict a reliability metric (like time to failure) based on specific parameters. Each failure model requires information about the part and the application in which the part is used. To illustrate this point, an analysis of the information required for the time dependent dielectric breakdown (TDDB) failure mechanism is presented.

TDDB is based on the thermal bond breakage at the $Si - SiO_2$ barrier due to the electric field that is generated in a transistor. Silicon – oxygen bonds are broken, leading to oxygen vacancy and generation of weak Si - Si bonds that weaken the oxide layer and result in eventual breakdown. This process is more prevalent with higher electric fields and higher temperatures which are the environmental stress factors. The form of the model and the explanation of the variables are provided in equation 6.

$$TTF = A_0 \exp(-\gamma E_{ox}) \exp\left(\frac{E_{aa}}{kT_j}\right)$$

where TTF is the time to failure of the device, A_0 is an arbitrary scaling factor, γ is the electric field acceleration factor, E_{ox} is the externally applied electric field, E_{aa} is the apparent activation energy for specifically TDDB, k is Boltzmann's Constant, and T_j is the junction temperature in kelvin.

Equation 6 can be altered by modifying the electric field into the ratio of the operating voltage and the oxide layer thickness of the part. Using this conversion, the model is now dependent on the part parameters of oxide layer thickness and activation energy (for TDDB), application condition parameters of junction temperature and operating voltage, and model parameters A_0 and γ .

The model constant values are part dependent and cannot be generalized. Extensive research has been completed on specific parts to determine model constants that accurately project the time to failure for TDDB [30]–[38]. Using this information, ranges on the modeling constants have been developed and summarized [14]. The ranges and modeling constants for four semiconductor wearout failure mechanisms and associated models are presented in Table 4. A detailed discussion on the modeling constants related to time dependent dielectric breakdown is shown in Chapter 3.

Table 4: Sample semiconductor failure mechanisms and associated models

Mechanism	JEP122H Model [14]	Constant Value Ranges
Time Dependent Dielectric Breakdown	$TTF = A_0 \exp\left(-\frac{\gamma V_g}{t_{ox}}\right) \exp\left(\frac{E_{aa}}{kT_{junc}}\right)$	$0 < \gamma < 2$ $0.3 < E_{aa} < .6$
Hot Carrier Injection	$TTF = A_0 I_{sub}^{-N} \exp\left(\frac{E_{aa}}{kT_{junc}}\right)$	$2 < N < 4$ $2 < E_{aa} < .4$
Negative Bias Temperature Instability	$TTF = \left[\frac{\Delta p}{A_0} \exp\left(\frac{E_{aa}}{KT_j}\right) V_{ge}^{\alpha}\right]^{\frac{1}{n}}$	Δp : Shift in Parameter $3 < \alpha < 4$ $0.15 < n < 0.25$ $01 < E_{aa} < .15$
Electromigration	$TTF = A_0 (J - J_{crit})^{-n} \exp\left(\frac{E_{aa}}{kT_j}\right)$	$\frac{3000}{l_b} < J_{crit} < \frac{7000}{l_b}$ $(l_b) \text{ is length of gate}$ $n \sim 2$ $0.5 < E_{aa} < 0.6$

Chapter 3: Information Requirements for Modeling

As explained in Chapter 2, the reliability of an electronic part is dependent on application conditions, part information, and modeling constants. Information related to each of these factors must be found (or approximated) for a proper reliability estimation to be made. As each input is treated as a distribution representing information uncertainty, the more information that can be found, the less uncertain the final to failure distribution will be. Each of three main input aspects is discussed below in the context of methods of collecting information and quantifying the uncertainty in the information.

Application Conditions

The reliability of a part is directly dependent on the application conditions in which the system is used and exposed too. The application conditions include environmental conditions such as temperature, humidity, and vibration, as well as operating parameters like voltage and current. As shown in the failure models from Table 4, temperature is key for estimating the time to failure, as well as other application parameters like threshold voltage or substrate current. Without knowing or approximating these values, the time to failure cannot be accurately determined.

Operating condition limiting values are provided for a part in a datasheet, webpage, or other document. Depending on the type of part and manufacturer, this information can be provided as a single value or given with upper and/or lower limits. However, this information should be used for designing and integrating the part into

the system, not for estimating the application conditions and reliability of the part. The actual usage of the part will not identically match the value or range of values. Whenever possible and information available, the reliability of a part should be evaluated based off of the *true* application usage. The different levels of information collected for determining application condition distributions are as follows:

- 1. Collect sensor information from actual application environment
- 2. Approximate temperature range using past knowledge.
- 3. Derated usage guidelines for a specific application and part
- 4. Approximate using maximum ratings for a specific part

Sensor Collected Information

One method of determining the actual application usage and conditions is through sensor monitoring. Unlike with using the datasheet nominal value, this method represents the actual usage of the part and can capture additional aspects that a single value cannot. A part will not always be exposed to the maximum rated temperature of usage for the entirety of the life of the part. To show the difference on a small scale, processor temperature data was collected for 14 minutes during usage and compared with the maximum temperature provided in the datasheet (results shown in Figure 5). Even during high usage, the part does not reach, let alone remain, at the maximum temperature value. Thus, using the maximum value to determine an actual reliability estimation is not valid. Additionally, a part's usage will depend on the requirements of the system and may not be powered or "turned on" at all times. Estimating the reliability

with a datasheet value will not effectively account for duty cycle operation or only partial usage.

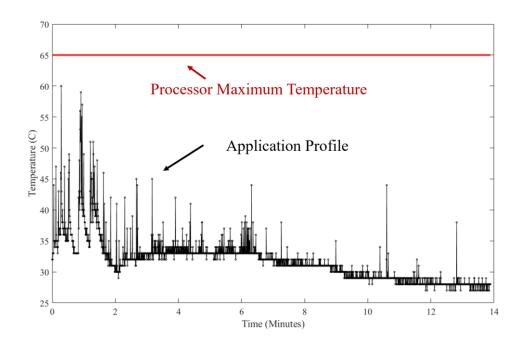


Figure 5: Processor temperature measured during usage compared with datasheet maximum value.

The method by which sensor information is collected and for which attributes varies depending on the system and application. If available, time series sensory data can provide specific information for application conditions over a device's lifecycle. For example, sensor information collected from cell phones is recorded either at period instances or a change in state with an associated timestamp [39].

The process of converting individual measurements of parameters to a distribution which can be sampled for reliability distributions is completed using a kernel density function. The process is completed using the following steps:

- Collect application condition information of interest over a certain length of time using sensors or other monitoring equipment.
- 2. Using the values from step 1, a kernel density function is used to approximate the sample distribution in incremental distances.

The kernel density function is dependent on the specific kernel that is used and a *bandwidth* parameter which controls the severity of the kernel. When a gaussian kernel is used, the *bandwidth* is the standard deviation that is put around each point in the dataset. Using the kernel density function method, the estimated density at any point x within the dataset X is shown in equation 7.

$$f(x) = \frac{1}{n} \sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right)$$

where K is the kernel function, n is the number of samples in the dataset, and h is the bandwidth parameter in the range of (0,1). A gaussian kernel is used with form shown in equation 8.

$$K(\alpha) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}\alpha^2\right)$$

The bandwidth parameter must be selected for each dataset individually. From equation 7, a lower bandwidth value means that the differences between x and x_i will be magnified and lead to a more complex, less smooth density estimation. If a high bandwidth value is selected, the differences between values will be smaller and a smoother function will be generated. Figure 6 shows a comparison of different bandwidth values for a gaussian kernel density on 2000 normally distributed values

with mean of 5 and standard deviation of 1. The blue line with h = 0.1 has a noisy function as it overfits to the individual samples, whereas h = 0.9 overly smooths the function and does not capture all of the underlying data.

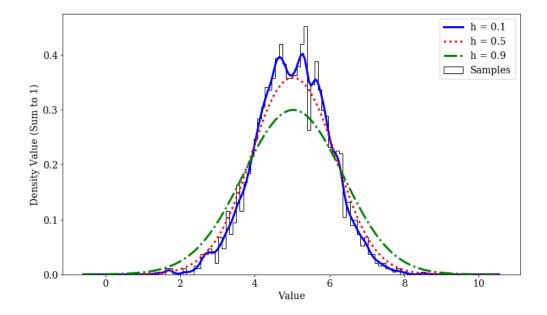


Figure 6: Comparison of different bandwidth (h) values on a gaussian kernel density function generated from 2000 samples with mean of 5 and standard deviation of 1.

Depending on the assumed kernel, there are rules that have been developed for selecting bandwidth values. For a gaussian kernel, there are two primary rules for determining the bandwidth value: Scott's Rule [40] and Silverman's Rule [41] (the equations below show the formula for determining a bandwidth value with these rules assuming a single series of data).

Scott's Rule:
$$h = n^{-\frac{1}{5}}$$

Silverman's Rule:
$$\left(\frac{3n}{4}\right)^{-\frac{1}{5}}$$

In practice, the kernel density function is determined at incremental distances (K) over the space of the input samples. The smaller the incremental distance, the finer the control over where the final samples will be selected from. 200 different increments were selected for evaluating the input application condition information and the kernel density at any increment k is labeled as $f_k(x)$.

3. Next, each kernel density value corresponding with each increment is converted into a Cumalitive distribution. The final increment will have a value of 1. The Cumalitive value at each increment *k* is provided in equation 11. The final value

$$F_k(x) = \sum_{j=1}^k f_j(x) \ \forall k = 1 \dots K$$
 11

- 4. Generate N uniformly random samples between [0,1] and determine which increment the random number falls in. The number of samples N determines how many samples will be used for the final time to failure distribution and should be the same for all of the inputs. Selecting which increment each random sample belongs to can be determined by finding the next increment value higher than the random sample value.
- 5. The selected increment's corresponding value is the final output sample value.

A visual representation of the conversion process is shown in Figure 7.

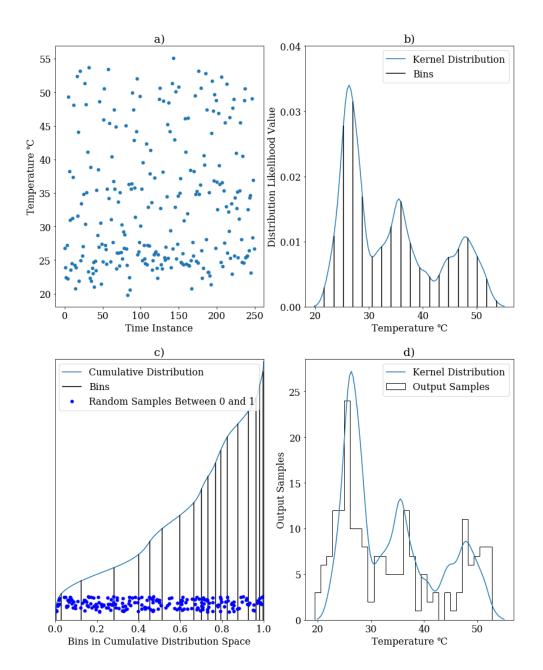


Figure 7: Process for converting input samples to output samples through distribution approximation. a) provides (randomly generated) temperature samples, b) shows the kernel distribution estimation and corresponding bins, c) converts the distribution into a cumulative form and shows randomly generated points between [0,1] and the corresponding bins that they fall in, d) shows the final sampled values compared with the kernel distribution.

To compare different kernels and bandwidth values on the distribution approximation methodology, temperature data was collected from a laptop processor (Intel I7-8550U) over 1400 seconds during normal usage. Figure 8 shows the time series temperature data that was collected.

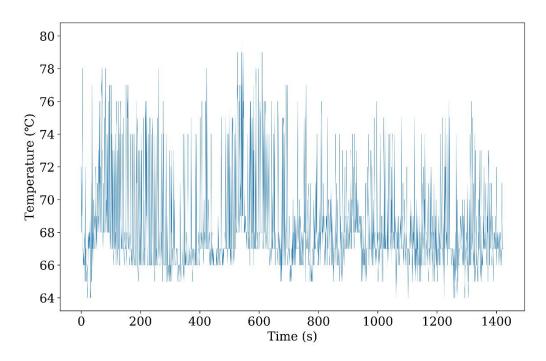


Figure 8: Collected temperature sample readings from Intel I7-8550U processor.

Using this information, the impact of the kernel bandwidth was evaluated. A guassian kernel was selected and the temperature range was split into single degree increments between the minimum and maximum value to match the precision of the temperature monitoring software. The resulting kernel distributions generated for different bandwidth values are shown in Figure 9. As expected, with a lower kernel bandwidth value the distribution is much more sensitive to changes. This leads to the situation in which the distribution is drastically dropping in between each discrete

measurement value which is not representative of the true application. As the kernel bandwidth value is increased, the kernel more closely represents the true distribution and then starts to over-generalize or smooth at high values (black line with bandwidth equal to 1).

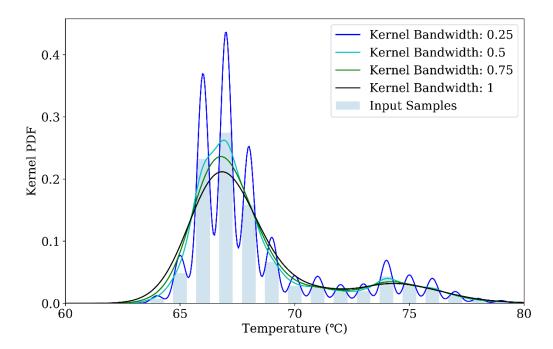


Figure 9: Comparison of different kernel bandwidths for approximating temperature distribution. Input samples histogram converted to a discrete probability distribution.

Additionally, analysis was completed to evaluate different kernels other than the gaussian kernel. Using the same collected temperature data a gaussian, exponential, and Epanechnikov kernel were selected based on their frequency of use in completing density approximation methods. For each case, the bandwidth was held as a constant at 0.5 and the results are shown in Figure 10.

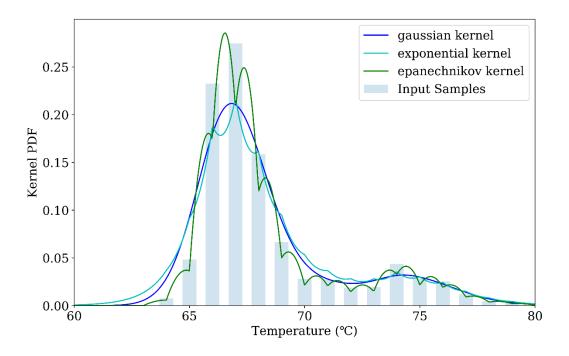


Figure 10: Comparison of different kernels for approximating a sample temperature distribution.

Derating Conditions Approximation Method

In many cases, collecting specific application data is not possible or efficient. For example, monitoring threshold voltage for individual transistors may not be possible or convenient. Estimating application conditions without a known profile or sensor information can be completed using standards and guidelines for specific applications. For example, NASA publishes derating guidelines for device parameters such as temperature, power dissipation, and voltage [42]. Example derating guidelines are shown in Table 5.

Table 5: Derating guidelines for transistors provided by NASA [42]

Stress Parameter	Derating Factor
------------------	-----------------

Power	0.60
Current	0.75
Voltage	0.75
Junction Temperature*	0.80

*Do not exceed Tj = 125 °C or 40 °C below the datasheet maximum rating.

Applying derating guidelines must be done considering the meaning of the parameter and the functionality of the part. For example, the same derating standard applies a derating guideline of 0.8 for power MOSFET gate voltage [42]. In theory, if the gate voltage drops below the minimum threshold value, the device will not turn on and the part will not function as intended. Utilize the part information before making any judgements with derating guidelines. As seen previously, the threshold voltage is also known to change with temperature and thus should also be considered when selecting a derating value [43].

The derating guideline limit is the upper limit on the application stress condition and is modeled by selecting a distribution with the same maximum value. This is like the situation in which only the part's maximum ratings are used. Selecting the form and values for the distribution depends on the application that the part is used in and will directly impact the reliability of the part. An application that is frequently near the upper derated limit or part rating will have a different distribution than a part in an environment which never approaches them. For example, PLC sensor circuity used inside a controlled environment manufacturing line may never reach the part or derating limits. However, a similar PLC sensor mounted outside on an amusement park ride may experience extreme temperature and vibrations near the derating or part limits.

The distribution for modeling the temperature of these applications is completely different.

A summary comparison of the different application condition methods is shown in Table 6. The table is sorted based on the quality in which the application condition will be modeled to accurately represent the true usage conditions.

Table 6: Comparison of application condition collection methods

Approximation Method	Advantages	Disadvantages
Time Series Data Collection	Most specific informationBest representation of actual application	Requires installation of sensors and collection of information
Previous Application Experience	Quick implementation which can adapt over time as more experience is gained	 Not as accurate modeling Requires selecting distribution form and attribute values
Derated Guideline Limitations	 Specific values provided in standards Does not require any additional hardware on systems to collect information 	 Not available for all applications or types of parts Requires selecting distribution form and attribute values
Part Maximum Ratings	Provided for almost every part	Is not related to the application and will not give reliability estimations related to actual usage.

Part Information Sources

The information that is available for a part depends on the type of part itself, the rating to which it is

Commercial Sources

Finding the part information for reliability assessment and modeling requires locating and analyzing many different documents. Traditionally, the datasheet is the primary document that is used to share information about a part, but a datasheet alone will not provide all the information needed. For all parts, many different documents are available that can be used for reliability modeling. A list of common documents provided and the types of information that can be found is provided in Table 7.

Table 7: Summary of information sources for COTS electronic parts

Data Source Type	Data Source	Applicable Information	Example Sources
93	Datasheet	 Part Ratings (Threshold Voltage / Maximum Substrate Current) Environmental Ratings (Temperature / Humidity Ratings) 	[44], [45]
Manufacturer Data Source	Qualification Report	Part DimensionsTesting Levels / Requirements	[46]
acturer D	Product Change Notification	Material CompositionPart Structure / Packaging	[47]
Manuf	Application Note	Expected Failure Mechanisms	[48]
	Manufacturer Reliability Testing	Reliability Report Data and qualification levels	[28]
Other Source	Industry Standards	Material Information, Qualification Testing Levels, Application Limits and Conditions	[42], [49]
Other	Research Papers	Model ParametersActivation Energy Information	[30]–[38]

The documents described in Table 7 will not be available for all COTS devices. This is one of the main restrictions of COTS devices as the consistency of information is not guaranteed. Alternatively, all non-COTS devices (such as military, space, or automotive qualified parts) should have the same standardized tests, requirements, and even information format. There is specific documentation associated with parts that are automotive, space, or military qualified [50], though the information within these can be found for COTS parts in some cases. A summary of the information that can be found from each commercial source is discussed in each of the sections below.

Datasheet

The classical document used for gaining part information is the part datasheet. The part datasheet outlines the performance parameters, operating conditions, physical dimensions, and other aspects depending on the type of part. Every part or family of parts will have a datasheet. Each datasheet typically includes the following sections: introduction, absolute maximum ratings, electrical specifications, part layout, contact information, and document updates. These sections will vary in name and order depending on the manufacturer, but these sections at minimum should be included in an effective datasheet. When compared to previous reports on part datasheets, datasheets now rarely include testing or quality data sections as these are in their own documents [51].

The introduction is the first section that provide a summary of the part. This includes the part number, which describes the specific part in question. Figure 11 shows the information provided through the part number for an Intel processor [52]. The

introduction will also include a basic description of the part, as well as the specific use or applications that the part can function in.

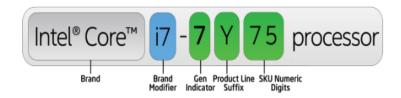


Figure 11: Information provided within the part number for an Intel processor [52].

The absolute maximum ratings provide the limiting values for the part. Analog Devices describes these ratings as "parameters that must not be exceeded [53]." These parameters vary depending on the type of part being used, but factors such as operating and storage temperature range, maximum power dissipation, thermal resistance, and some voltage and current limits will typically be included. Most datasheet includes a comment below the absolute maximum ratings warning that these are "stress-based" ratings and that exceeding these ratings can result in immediate part failure. These specifications are the maximum ratings that can be used as a worse case scenario when modeling application condition distributions.

The recommended or electrical specifications provide the values for the key parameters of the device. The range of these values is where the performance of the part is guaranteed. As long as the system parameters do not exceed what is listed in this section, the system should perform properly and not experience immediate reliability concerns (such as overstress). This can also include charts that determine how one

parameter is impacted by another parameter, such as temperature [43]. This information is useful for design but can also be used for part parameters.

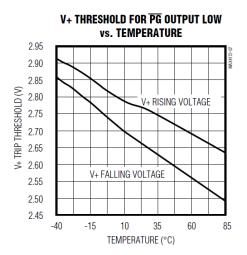


Figure 12: Sample curve of the impact on turn on voltage with respect to temperature [43].

Part Webpage

The part webpage serves as an introduction to the part and gateway for more detailed information through downloadable documents and other linked pages. Each part manufacturer has their own style of part information page which will vary but are usually consistent within a single manufacturer. The page traditionally feature at least a link to the datasheet, some basic ratings and features, a set of documents associated with the part, and an image of the part. Vishay Siliconix (part SIS415DNT) has specific sections on specifications, documents, design tools, quality, and a place to request samples or ask questions [15]. Texas Instruments provides similar information for part CSD17318Q2 but also includes the status (active vs. obsolete) and similar parts [55].

Unlike with datasheets or other .pdf files, part information webpages are easily searchable and allow for compilation of information quickly.

Qualification Report

The qualification report for a specific part provides more detailed information about the part, specifically including information from different tests that have been completed on the part. This testing can include thermal, electrical, and physical testing and characterization of the part that is completed by the manufacturer [56]. In addition to testing results, more rigorous material composition of the packaging and die structure can be provided. While very useful, qualification reports are not provided for all parts within a company, and thus cannot be used as a reliable method for collecting information.

Application Notes

Application notes provide specific insight by the manufacturer for usage of parts in a specific application. This can include how to integrate the part into a specific circuit, mount the device properly, or understand the thermal properties of a device. Application notes can be part specific or related to families of parts. A web scraping analysis was completed based on the Vishay and ON Semi technical libraries, which contains application and technical notes covering their products. The pages feature a table of application note files across all types of parts. By analyzing the title string for each document, the information content can be determined. Table 8 shows the most frequently found words in the titles of the strings for both manufacturers. The most common term was "Power" for both manufacturers. There are also several different

part types such as MSOFET, Resistor, and Capacitor that frequently have application notes published. Others include terms like "Thermal" or "Mounting" which give ideas about the content of the actual application notes.

Table 8: Most common terms and their frequency of occurrence in Vishay and ON

Semi Technical Libraries

Vishay (285 Notes)		ON Semi (1426 Notes)	
Term	Percentage of Notes (%)	Term	Percentage of Notes (%)
Power	16.84	Power	14.31
Resistors	11.23	Design	9.33
MOSFET	9.82	Driver	7.57
Mounting	9.82	Converter	6.03
Instructions	8.07	Board	5.75
Capacitors	6.67	Evaluation	4.42
Film	6.32	Motor	3.86
Converter	4.91	High	3.79
Voltage	4.56	MOSFET	3.72
Thermal	4.56	Supply	3.58
Modules	4.21	Voltage	3.44
Guidelines	3.86	Series	3.09

The titles of the application notes from both manufacturers show that certain aspects like Power and MOSFET are frequently discussed. Vishay notes tend to have more part type specific notes (with terms like Capacitor, Resistor, Module) then ON Semi. The most common term for both part manufacturers was Power and may of the notes were related to power management solutions.

Product Change Notifications (PCNs)

Product Change Notifications (PCNs) are documents issued by the manufacturer that detail any change in the construction, operation, or capabilities of the

device. PCNs can provide information regarding a change in manufacturing location, a change in material composition, or an altering in the expected performance parameters for the part due to updated testing or other changes. Unlike for datasheets or qualification reports, PCNs will typically be for a range of products provided by the manufacturer, and not an individual part. At a bare minimum, a PCN must include a unique code or number for identification, a definition or classification of the proposed part changes, the timing for when the change will occur, the deliverables to the customer, and record retention requirements [57]. PCNs can be utilized in the part selection process for both initial selection and long-term considerations. The initial selection process can require information that can only be found in a PCN for the part, and long-term evaluation for monitoring if the part still maintains the required performance levels for the application. For example, a PCN released by Altera reports on the changing of both the epoxy mold compound and bond wire material for specific BGA packages [58].

Commercial Part Information Templates

Templates have been developed to allow for the entry of information based on the requirements for specific failure mechanisms. Each template is based off a transistor (MOSFET or IGBT) and is split into aspects based on part parameters and application information. As an example, the template part and application condition information requirements are provided in Figure 13 and Figure 14 respectively.

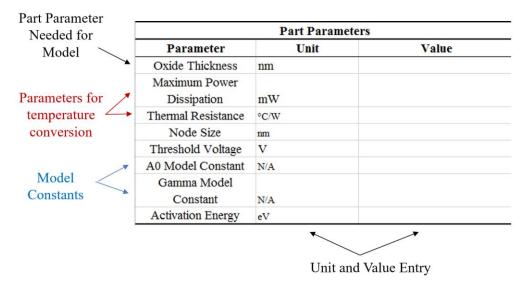


Figure 13: Part information required for failure mechanism template (TDDB)

The part information required for the template is the combination of part material and geometric features, datasheet parameters, and modeling constants. By using part specific features, the reliability estimations are also part specific. For the TDDB case, the only geometric feature is the oxide layer thickness of the device. The other datasheet parameters can be used for estimation of other parameters in multiple methods. One method is to use these values as approximations for unknown application information. An example of this is using the maximum power dissipation for the device to approximate the actual power dissipation the part will experience. Another method is to use relate information about this part to other similar parts. Then, any unknown information from the original part can be approximated using information from similar parts. This assumes that parts with similar information and design will have similar reliability if all else is consistent.

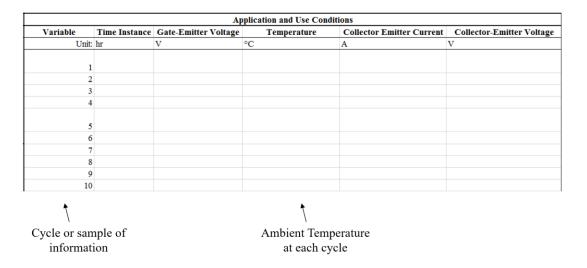


Figure 14: Application condition information for failure mechanism template

The application information portion of the template is designed to allow the entry of information over a period or cyclic fashion. This will allow for a much better representation of the application environment and thus reliability estimations. In the example of TDDB (see Figure 14), the "Gate-Emitter Voltage" column is used for determining the electric field parameter in the model and the "Temperature" column is used for the temperature parameter. The final two columns are used for determining the actual power dissipation of the device. These columns would be different for different device types. At each increment of time, this information can be entered to form a distribution around the parameters.

Node Size Approximation Method

When information is not provided or cannot be found, other methods have to be used to determine the input distributions. Approximation of part information can be completed using the device node (or feature) size. The node size is the minimum channel length of a transistor within a processor or other device. This is typically provided in relation with the description of a processor (such as a 7 nm technology), although the name for a processor does not necessarily represent the actual node size for the part [59]. The node size is associated with Moore's law which described the doubling of the number of transistors (and thus reduction in transistor size by 2) each year. Figure 15 shows the most recently developed node size each year frm 1970.

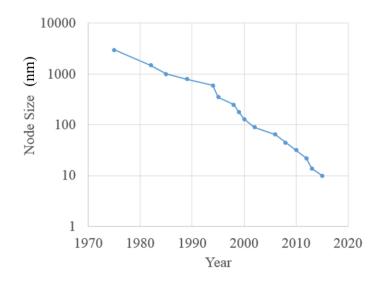


Figure 15: Change in most currently developed node size in each year.

Because many of the required properties for failure mechanism models are geometric, the node size can be used to determine an approximation or range on the value. This includes properties like the gate height and gate oxide layer thickness which are properties needed for failure models and cannot be easily found. By analyzing reports from device manufacturers, the change in these properties in relation to node size has been completed (see Figure 16 for an example based on the gate oxide thickness layer).

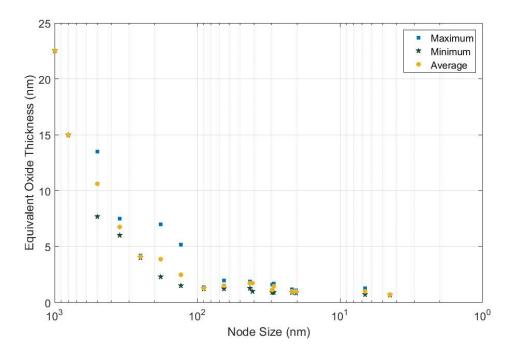


Figure 16: Change in oxide layer thickness in relation to node size.

Uncertainty is introduced when the approximation method is used for properties by approximating a normal distribution based on the known values from the technology reports. This means that a part with a known oxide thickness will have less variation in the input when compared to a part where the oxide thickness is unknown and is approximated using the node size. This follows the same basic principle that when more specific information is known, the level of uncertainty is reduced. For this process, it is assumed that the node size is based off of the *smallest* node size on the die in the instance where multiple different sized transistors are used.

Higher Grade Part Information

Automotive parts that meet the qualification requirements of AEC (Automotive Electronic Council) or space parts qualified to SAE AS9145 must complete a

production part approval process (PPAP) [49], [60]. The PPAP documentation originally started with the automotive industry but has moved to space parts [61]. This process requires documenting of the design, manufacture, and status of a part to the customer. Each PPAP document contains 18 - 20 sections including material information, qualification testing results, and design / process failure mode effect analysis [49], [62]. This information is useful for comparing parts and can be used to better understand the expected reliability of the part. This is a prime example of information that is expected for non-COTS parts but will not be found for COTS parts.

The availability of PPAP documentation varies for parts and manufacturers. This was evaluated by analyzing all of the MOSFETs provided on the Diodes Inc. website [63]. In total, Diodes Inc. has 1174 MOSFETs, 179 of which are rated as commercial (COTS) and the remaining 995 are automotive parts. Figure 17 shows the results of the analysis. Of the automotive parts, 19% do not provide a PPAP document, 48% provide a PPAP document with an additional request, and the rest have a direct link to the PPAP document. None of the 179 COTS MOSFETs have a PPAP document associated with them.

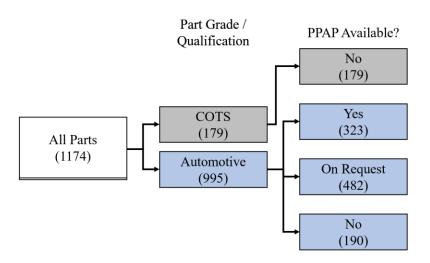


Figure 17: Availability of PPAP documentation for Diodes Inc. MOSFETs

A PPAP document provides a consolidation of information from a sole source that cannot be found for COTS products; however, some of the information found in this document is correlated with documents that *can* be found for COTS devices. For example, one PPAP section requires qualification test results which can also be found through a qualification testing report [46], although the same level of analysis is not completed. This shows that, while not as convenient as a PPAP, other documents can be used to find similar levels of information.

The current method by which military-grade parts are released by part manufacturers is through qualification with MIL-PRF-38535. MIL-PRF-38535 has different qualification requirements dependent on the application requirements or type of part which are designated by different QML (qualified manufacturer list) classes [64]. The standard was developed as a replacement for the Qualified Products List (QPL). Under QPL, individual part designs had to meet specific qualifications. QML is instead based on qualification of specific production lines and designs by specific

manufacturers. Overall, this resulted in lower total qualification time in a hope to increase the usage by part manufacturers. Table 9 displays the different QML qualification levels (with classes lower in the table corresponding to higher qualification requirements).

Table 9: MIL-PRF-38535 QML Class and Descriptions

QML Class	Specification	
M	Vendor Self-Verification Parts	
N	Plastic Parts	
Q	Hermetic Parts	
V	Radiation-Qualified Hermetic	
l v	Parts	

The QML qualification class is critical for evaluating a part, and just assuming that a part that is MIL-PRF-38535 qualified will have the expected reliability and performance is incorrect. NASA only considers QML Class V parts to be "low risk" for space applications, and considers classes M, N, and T to be "high-risk" parts [65].

Depending on the qualification class, different testing and reporting requirements must be met. Many tests are based off of industry standards or use test methods from MIL-STD-883. MIL-STD-883 provides test methods for standard microelectronic devices. Table 10 shows example test methods that are used to qualify electronic parts for specific tests.

Table 10: Example standards for different military test qualifications

Test/monitor	MIL-STD-883 test method (TM) or industry standard
Wafer acceptance	TRB plan (see H.3.2.3)
2. Internal visual	TM 2010 or in accordance with manufacturers internal procedures
Temperature cycling/thermal shock	TM 1010/TM 1011
Resistance to solvents	TM 2015
5. Bond strength	TM 2011
6. Ball shear	ASTM F 1269
7. Solderability	TM 2003
8. Die Shear or stud pull	TM 2019 or TM 2027
Steady-state life test Endpoint electricals	TM 1005 In accordance with device specification
10. Physical dimensions	TM 2016
11. Lead integrity	TM 2004
12. Inspection for delamination	e.g., TM 1034 (dye penetrant), cross-sectioning, C-mode scanning acoustical microscopy (CSAM), etc.
13. Highly Accelerated Stress Testing (HAST)	100 hours, +130°C, 85% relative humidity (RH) 2/
14. Autoclave	JESD 22-A102 (no bias) 2 atm., +121°C
15. Salt atmosphere	TM 1009
16. Adhesion to lead finish	TM 2025
17. Interim pre burn-in electricals	In accordance with device specification
18. Burn-in test	TM 1015, 160 hours at +125°C or manufacturers QM plan
19. Interim post burn-in electricals	In accordance with device specification
20. Percent Defective Allowable (PDA) or alternate procedure for lot acceptance	1% PDA or manufacturer's QM plan
Final electrical tests (see table III, herein, for definition of subgroups) a. static b. dynamic c. functional d. switching	In accordance with device specification
22. External visual	TM 2009 or JESD 22-B101 or manufacturers internal procedures

Modeling Constants

Modeling constants are needed to make failure models generalizable for different parts or usage conditions, and each part will have specific constants. The bestcase scenario is when these specific constants are provided for a part. This situation is unlikely to occur, and thus other methods must be developed to estimate or determine them. One solution is to complete a set of experiments with varying environmental conditions and part parameters to determine the modeling constants for a specific part. This process is not usable when dealing with many different parts within a system due to the time and cost requirements associated with physical testing.

Another method is to evaluate modeling constants by analyzing the results information provided within research papers. This process must be completed based on a specific failure mechanism (and thus failure model). Instead of completing tests separately, the modeling constants are determined by completing an optimization problem to fit the failure model to the data found in a research paper. Part parameters and application condition information are taken from the documents and used as the inputs to the optimization problem. Table 11 shows sample information collected from research papers related to the TDDB failure mechanism with each shaded region representing a different part that analysis was completed on.

Table 11: TDDB Time to failure data collected from research papers for TDDB (each region are results from a different part).

TTF(s)	Vg (V)	Tox (nm)	$\frac{E_{ox}}{(\frac{MW}{cm})}$	Temp (K)
1932.78	3.78	2.00	18.92	300
17394.41	3.63	2.00	18.13	300
156000	3.44	2.00	17.19	300
3159.11	4.51	3.00	15.02	300
278.59	4.74	3.00	15.80	300
21.50	4.98	3.00	16.60	300
200.99	4.96	3.40	14.58	300
22.40	5.20	3.40	15.29	300

TTF (s)	Vg (V)	Tox (nm)	$\frac{E_{ox}}{(\frac{MW}{cm})}$	Temp (K)
14994.29	3.21	1.40	22.95	300
2448.44	3.31	1.40	23.63	300
118.60	3.51	1.40	25.04	300
29.04	3.60	1.40	25.75	300
1.56	3.81	1.40	27.20	300
0.06	4.00	1.40	28.57	300

Modeling was completed on a per part basis using linear least squares optimization. For the example of TDDB, the optimization takes on the form of equation 12. The minimization was completed using the *lmfit* software package within Python. The optimized model constant values were then used to predict the time to failure as validation. Figure 18 shows the final projected time to failure for one part compared with the actual time to failure.

$$\min_{A_0,\gamma} \epsilon(A_0,\gamma) = \frac{1}{2} \sum_{i=1}^n \left(TTF_i - A_0 \exp\left(\frac{\gamma V_g}{t_{ox}}\right) \exp\left(\frac{E_{aa}}{kT_j}\right) \right)^2$$
12

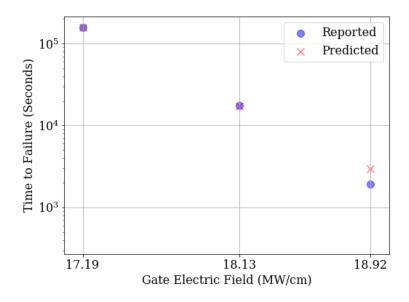


Figure 18: Predicted vs actual time to failure using optimized model constant values.

Time Dependent Dielectric Breakdown Modeling Constant Analysis

The electric field for the part can be found by dividing the part operating voltage by the oxide layer thickness. Sample values for the operating voltage, oxide thickness, and subsequent electric field are shown in Table 12. This information was found from multiple technical documents published by intel for each new part node size [33].

Table 12: Impact of Node Size on Electric Field Parameters [33]

Node Size	t_{ox} (nm)	V_{comp} (V)	$E_{ox}\left(\frac{MV}{cm}\right)$
350 nm	6.9 - 8.1	3.6	4 – 6
180 nm	3.5	1.8	5
130 nm	2.2	1.2 - 1.5	5 – 7
90 nm	1.2	1 - 1.2	8 – 10
65 nm	1.2 - 1.6	1	8 – 10
45 nm	1	1.1	10 – 15
20 nm	1.1	0.9	8 – 11
7 nm	0.85	0.7	8 – 12

As seen in Table 12, the electric field increases with decreasing node size. Based off the thermo–mechanical model, the expected time to failure will decrease with increasing electric field, and thus TDDB wearout becomes a larger concern as smaller node size parts are implemented. In addition to the electric field, the relation of electric field and activation energy has been analyzed by correlating the activation energy with the effective dipole moment and enthalpy of formation for the SiO_2 bonds in question (13).

$$E_{aa} = (\Delta H)_o - aE_{ox} \tag{13}$$

where E_{aa} is the apparent activation energy for TDDB, $(\Delta H)_o$ is the enthalpy of activation for bond breakage, a is the effective dipole moment for the bond breaking, and E_{ox} is the externally applied electric field.

Based on the energy level for the SiO_2 bond in question, which correspond to specific electric field ranges, there are values for the effective dipole moment and enthalpy of formation required to break the bond. These values, along with the specific electric field for the part in question, can be used to determine the activation energy for the part [38]. Table 13 shows the resultant values and usable electrical field range for the low and high energy levels. Figure 19 shows the two different energy levels and corresponding impact on activation energy, as well as the transition period between the two [38]. The activation energy has also been directly related to the node size of the part, as seen in Figure 20 [38].

Table 13: Modeling Parameters for activation energy [38].

Energy Level	Usable Electric Field Range $\left(\frac{MV}{cm}\right)$	$lpha\left(e\dot{A} ight)$	ΔH_0 (eV)
Lower	9 – 13 (and Higher)	13	1.95
Higher	3 – 5	7.4	1.3

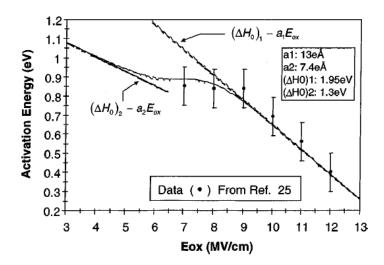


Figure 19: Relation of activation energy and electric field over two different bond energy levels.

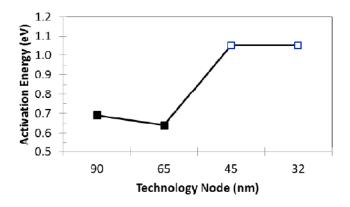


Figure 20: Relationship of activation energy and node size

The relationship between the electric field and gamma (field acceleration parameter) has also been analyzed. The equation used for determining the effective gamma parameter is shown below [38]. The same alpha values apply for correlating the first two levels of energy in bond breaking. Figure 21 shows the two different energy level models for different electric fields and relates the gamma parameter and part temperature.

$$\gamma_{eff} = \frac{\alpha_m}{k_B T} \tag{14}$$

Table 14: Usable temperature range and corresponding α value for different energy levels [38].

Energy Level	Usable Temperature Range (K)	$\alpha\left(e\dot{A}\right)$
Lower	600 - 1000	13
Higher	0 - 200	7.4

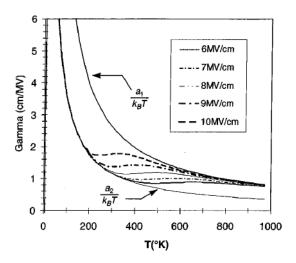


Figure 21: Relation of gamma parameter and temperature over different electric fields and energy levels [38].

Suehle and Chaparala also analyzed the relationship between the gamma parameter and the applied temperature as well as adding the oxide thickness level as another parameter [66]. Figure 22 shows the results from this study. This result seems to contradict the result found in Figure 21. With this study, there does not seem to be a definitive relationship between the gamma parameter and the part temperature, whereas a trend does exist for [38]. This discrepancy may be explained by the temperature ranges that were used during testing. In [66], the range of temperatures aligns with the transitional period found in [38] where neither of the two energy level models aligns with the resultant gamma parameter value.

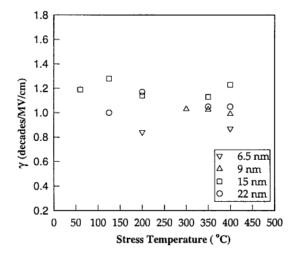


Figure 22: Relation of gamma parameter, temperature, and oxide layer thickness.

Chapter 4: Information Availability Metrics

Determining the consistency and quality of information provided by part manufacturers is a key aspect for evaluating part level reliability. If information is not available, assumptions must be selected which can lead to more uncertainty in reliability projections. A sample part from four different part categories (all from Vishay) were analyzed based on the types of documents that were provided (and thus different information provided). The results of this analysis are shown in Table 15. Compared with the other parts, the information associated with the MOSFET was the highest. In all cases, different documentation and information were provided. The only document and associated information provided in at least 3 of the parts was the datasheet.

Table 15: Comparison of Information Provided for Vishay COTS Parts

Part Type	MOSFET	LED	Optocoupler	Thyristor
Provided Information	 Datasheet Markings Package Drawing Pad Guidelines Thermal Models Reliability Data Tape Info Tech Tips SPICE Models 	• Datasheet	 Datasheet 3D Models Application Note Certificates 	 Datasheet Application Note Package Drawings

Additionally, a web scraping algorithm was used to evaluate the consistency of information for MOSFETs manufactured by Infineon. The information for 1410 MOSFETs from Infineon was collected from the searchable spreadsheet on the Infineon webpage [67]. A summary of the availability of information for the MOSFETs based on key parameters that define the part and are related to the reliability is shown in Table 16.

Table 16: Information Availability for Parameters from Infineon MOSFETs Part
Selection Table

Category	Percentage of Parts (1410)
Minimum Temperature	36.80%
Maximum Temperature	36.50%
Power Dissipation	88.10%
Drain-Source Voltage	99.90%
Thermal Resistance	21.90%
Gate Voltage	11.10%
Technology (node size)	98.10%
Package Type	100%

The device technology, package type, and drain source voltage were found for almost every MOSFET. Power dissipation values were found for 90% of parts while thermal resistance values were found for only 20% of parts. The most interesting result was that temperature was only provided for 36% of the parts and gate-source voltage was only listed for 11% of samples in the searchable database. Because this process was collected in an autonomous fashion in a searchable database, some of the missing information may be on the individual part pages or within documents. A more thorough

algorithm that collects from each individual page may produce different information availability results.

Metrics have been developed to evaluate the information availability provided by manufacturers, for part types, and for specific parts. These metrics can be used for evaluation of manufacturers and incorporated into failure time estimation. The development of these metrics is completed based off of information that is readily available by manufacturers on the part webpage, but can be updated and expanded based on additional information collection methods and contact with the manufacturer.

Thermal Information Availability (TIA)

Thermal information is needed for determining if the part can meet the application requirements of the final system. The primary thermal information associated with a part is the operating temperature range, storage temperature range, thermal resistance, and power dissipation. The thermal information availability (TIA) metric is based on evaluating how much of the above information is provided for a specific part. This metric has been designed as the product of three specific multipliers and is based on a scale between 0 and 1 (metric form is provided in equation 15). The best possible rating is 1 where specific absolute, recommended, and storage temperature ratings and associated locations are provided, as well as power dissipation and thermal resistance conversion parameters. A metric result of 0 is obtained if no temperature ratings are provided for the part.

$$TIA_{part} = (Location)(P_{diss} \& R_{therm})(Ratings)$$

15

Initial determination of these values for a part is based off of the part datasheet but can be changed depending on additional information that is found for the part, such as through communication with the part manufacturer or through analysis of research papers. The multiplier factor levels are determined subjectively and a process for continued evaluation and adjustment is provided at the end of the metrics section.

Table 17: Location multiplier levels

Location Description	Multiplier
Specific Location	1.0
"Operating" or "Specified"	0.2
No Description	0.01

Table 18: Thermal resistance & power dissipation levels

Power Dissipation Provided	Thermal Resistance Provided	Multiplier
*	*	1.0
	*	0.8
*		0.5
		0.1

Table 19: Temperature rating multiplier levels

Absolute Temp. Rating	Recommended Temp. Rating	Storage Temp. Rating	Multiplier
*	*	*	1.0
*	*		0.9
*		*	0.8
	*	*	.75
*			.6
	*		.5
		*	0.1
			0

Table 17 provides the multiplier values based on the temperature location information provided in for the part. The best result for this multiplier is a specific location, such as junction, ambient, or case (see Figure 23 for relative locations on part). By providing this information, there is true meaning behind the temperature rating and it can be compared with other parts or converted to other locations within the part. Providing this information is rewarded with a high multiplier value. The second level is when only an "operating" or "specified" term is listed with the temperature rating. This results in a much lower multiplier factor because neither of these terms provide an identifiable location on the part. The worst multiplier level is when no location identifier is specified, and thus the multiplier value is the lowest possible value. This level of granularity was selected, but further details can and should be provided. If a case temperature is provided, detailing how and where on the part the case temperature applies is more informative than simply stating case temperature. In a similar fashion, an ambient temperature rating without a qualifying factor on how the measurement was taken is less valuable than one in which a specific distance from the part where the temperature was monitored is provided.

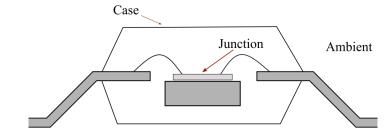


Figure 23: Common temperature measurement locations in a part.

Table 18 provides the multiplier levels for the power dissipation (P_{diss}) and thermal resistance (R_t) conversion information availability. This information is needed for completing the thermal design of the system and converting the temperature rating to different locations on the part. A common thermal resistance value is the conversion between the junction and ambient temperature value. This method is normally used for approximating the junction temperature from an ambient temperature, total power dissipation, and thermal resistance value [68].

$$T_i = R_t P_{diss} + T_a 16$$

The top multiplier level is when both the power dissipation and thermal resistance values are provided. The next best level is when only a thermal resistance value is provided. While knowing the maximum power dissipation is preferred, the power dissipation can also be determined using other parameters of the device and application. The next best case is when only a power dissipation values is provided. Without the thermal resistance parameter, the temperature conversion between different locations on the part cannot be completed. The worst case scenario is when no power dissipation or thermal resistances values are provided.

The final multiplier factor is the actual temperature ratings themselves (shown in Table 19). The value of this metric is based off of the number of different ratings provided in the part datasheet, or other documentation. The three ratings included are absolute, recommended, and storage temperature ranges. The best possible multiplier value occurs when specific ratings for all three are given, allowing the user to understand the application limits for storage, normal usage, and absolute maximum

usage. As less information, or less detailed information is provided, the metric multiplier value decreases. Preference is given to absolute maximum ratings as those are the most common temperature ratings to be provided, and thus it is heavily penalized if this rating is missing. At this level the temperature rating values themselves are not impactful on the TIA value, though situations can arise where this would need to be further evaluated. For example, thermal uprating of parts is completed between the recommended and absolute temperature ratings for a part. If the recommended and absolute temperature rating are the same value, thermal uprating is not possible using the currently developed methods and reduces the value of the information.

The current limitation with the metric is that it is fundamentally based on just the availability of the information and is not evaluating the information itself beyond the location parameter. This means the metric does not consider a case where overspecification of parameters is provided, like when the maximum temperature rating, maximum power dissipation, and thermal resistance values do not correctly align. Additionally, the metric currently does not evaluate if the information's accuracy. A manufacturer can provide information without completing validation or analysis to verify it. This can be addressed in future implementations by including additional information such as qualification testing to validate the information itself.

Material Information Availability (MIA)

Like thermal information, material information is also needed for evaluating parts and manufacturers. This information can be used for identifying bond wire

material and determining mold compound or die attach composition. The material information availability (MIA) metric is based on evaluating the ease with which material declaration information can be found for a part. IPC 1752 is a standardized format provided for sharing material information between the part manufacturer and the user. The format was designed to be flexible and supports several types of parts [69]. The standard format provides specific elemental composition, Chemical Abstracts Service (CAS) numbers, and weight percentages for each part aspect such as the die, lead frame, or encapsulant. It also features additional information like RoHS status and moisture sensitivity level (MSL). Figure 24 shows a sample IPC 1752 document for a MOSFET from ON Semi [70].

Homogeneous Material	Weight	Unit of Measure	Level	Substance	CAS	Exempt	Weight	Unit of Measure
Die	5.93	mg	Supplier	Silicon (Si)	7440-21-3		5.93	mg
Die Attach	2.353	mg	Supplier	Silver (Ag)	7440-22-4		0.059	mg
			A	Lead (Pb)	7439-92-1	7a	2.176	mg
			Supplier	Tin (Sn)	7440-31-5		0.118	mg
Lead Frame	152.108	mg	Supplier	Tin (Sn)	7440-31-5		2.06	mg
			В	Nickel (Ni)	7440-02-0		0.048	mg
			Supplier	Copper (Cu)	7440-50-8		150	mg
Mold Compound-Black	129.0	mg	Supplier	Ortho Cresol Novolac Resin	29690-82-2		25.8	mg
			Supplier	Carbon Black (C)	1333-86-4		1.29	mg
			Supplier	Fused Silica (SiO2)	60676-86-0		101.91	mg
Wire Bond - Al	2.44	mg	Supplier	Aluminum (Al)	7429-90-5		2.44	mg

Figure 24: Sample IPC 1752 document for MOSFET [70].

The MIA metric was designed to evaluate how easy it is to access material information. Many manufacturer websites require additional work like direct communication or account creation before access to specific documents can be completed [71]. Ideally, this information should be available in the part datasheet or on the part information page. The quality of the information presented must also be considered during the evaluation process. More specific or detailed material information affords a better representation of the part and improves the analysis and understanding of the part. Based off these factors, the metric has the following form.

The multiplier levels for the access and content factors are presented in Table 20 and Table 21 respectively. The MIA metric is also based on a scale between 0 and 1, where 1 represents the best material information availability.

$$MIA_{part} = (Access)(Content)$$
 17

Table 20: Access multiplier levels

Access Description	Multiplier
Available on part information page	1.0
Available on reliability or another searchable	0.8
page	0.8
In datasheet or another document	0.6
Requires account creation	0.5
Requires email or other manual contact	0.2
No access	0

Table 21: Content multiplier levels

Content Description	Multiplier	
Official IPC 1752 document format	1.0	
Material information presented in table (not	0.9	
IPC 1752 format)	0.9	
Specific RoHS document or detailed non-table	0.3	
information	0.5	
RoHS symbol	0.1	
No Information	0	

As previously discussed, the access multiplier evaluates how easily material information can be found for parts from a manufacturer. The best-case scenario and highest multiplier level is when the information or document link is found directly on the part page. The next best level is when the information is on a reliability page where specific part numbers can be searched for. Both methods do not require the effort of making an account or having to contact technical support and thus receive higher

multiplier levels. The most heavily penalized case is when a direct email or technical form must be completed. This method does not guarantee getting any material information and will take a much longer time. Due to these factors, the MIA value for a part requiring an email is heavily penalized.

For the content multiplier, the highest value occurs when the IPC 1752 official format is used. This can be in any file format that is supported by the standard, such as .xml, .csv, or .pdf. A 0.1 reduction in value is applied when specific material information is applied but it is not in the official IPC 1752 format. A much higher penalty is applied when non-tabular information is supplied, such as RoHS compliance, without specific elemental compositions. The worst case is when there is no material information available for the part, in which case the multiplier level and MIA value overall are 0.

Metrics Value Usage

Both metrics are evaluated on a per part basis and can be used for reliability estimation at a part level, comparison of individual parts, or generalized for evaluation and comparison of different part manufacturers. The sections below will describe how the metric values can be used for each of the methods presented above.

Reliability Estimation Incorporation

The determined metric values represent the level of confidence in thermal or material information that is available for a part. This confidence can be converted to an uncertainty level for specific parameters in reliability models. A part with a *higher* MIA

or TIA value (more information available) implies that the parameters related to this information will have a *lower* level of uncertainty. Alternatively, parts that do not have a high level of information availability will have higher uncertainty levels in parameters and thus a wider failure distribution.

One implementation of this is through the conversion of the temperature level from an ambient to junction location. The model temperature requires being evaluated at the point of failure, which for all die level mechanisms is the junction temperature. The application conditions will generally be provided in terms of an ambient temperature of the entire system. Equation 16 can be modified to include uncertainty terms as follows:

$$T_i = X(T_{amb}) + [N(\overline{R_t}, \beta) * X(P_{diss})]$$
18

where $X(T_{amb})$ is a generalized ambient temperature distribution, $X(P_{diss})$ is a power dissipation distribution, $\overline{R_t}$ is the mean thermal resistance value determined through the datasheet, comparison with similar parts, or other method, and β is the uncertainty in the thermal resistance.

The ambient temperature and power dissipation distributions are determined based on collecting information from the application environment. Determining the thermal resistance uncertainty is much more difficult and is not provided by the manufacturer. The TIA value can be implemented to provide an estimate on the uncertainty in the thermal resistance. Using the method provided in equation 19, the uncertainty in the thermal resistance will be minimized when TIA is maximized.

$$\beta = \frac{\overline{R_t}}{q} [1 - TIA] + \alpha \tag{19}$$

where $\overline{R_t}$ is the best estimate on the thermal resistance (typically value provided in the datasheet or parts with the same package type), α is the minimum uncertainty level 'po and q is a severity factor that controls the magnitude of the uncertainty and is defaulted to 100 (or the noise will be related to 1% of the expected value).

Comparison of Parts

The benefit of using the metrics for comparison of parts is that it provides a standardized method of evaluating the information provided for a part irrespective of the manufacturer or method in which the information is presented. Without the metrics, it can be difficult to compare parts without knowing what information is expected regarding thermal or material parameters. The metrics also combine multiple aspects into a single, comparable factor. In addition to the final metric, individual aspects of each of the metrics can be compared to get a more specific analysis, such as comparing the ratings multipliers of different parts. Some comparisons of parts are provided in the case study presented later in this thesis.

Any method can be used to compare the metric values between parts such as cosine similarity or Euclidian distance. These methods combine both of the metrics and result with a single value relating two parts. Cosine similarity is used when the magnitude of the values is not important, whereas Euclidian distance incorporates the actual values. When using the metric values, the Euclidian distance method makes more intuitive sense.

$$Dist(x \to y)_{EUC} = \sqrt{(x_{TIA} - y_{TIA})^2 + (x_{MIA} - y_{MIA})^2}$$
 20

$$Dist(x \to y)_{COS} = \frac{(x_{TIA}y_{TIA} + x_{MIA}y_{MIA})}{(x_{TIA} + x_{MIA})^2 + (y_{TIA} + y_{MIA})^2}$$
 21

Generalization and Comparison of Manufacturers or Part Types

It should not be assumed that all parts from the same manufacturer will have the same amount of information provided or final metric values. A prime example of this is commercial vs. military or space grade parts that may present information through different documentation [9], [10]. Part manufacturers also produce parts of several types and structures and may have different methods of presentation and content for each. Part manufacturers are also commonly involved in mergers and the consolidation of the market can lead to large problems with information consistency and availability [72]–[74]. Before a merger, each manufacturer has their own baselines and standards for information to be shared which may not be aligned or resolved after the merger. Any analysis completed on a manufacturer must be re-evaluated after any change in status. These reasons show the strong need for evaluating information availability metrics at a part level but also promote comparisons of information both within and outside the same company.

The generalization of metric values can be completed over many scales if proper considerations are put in place. The metric could be generalized for all parts within a specific category such as all power IGBTs or LEDs with a specific package. More broadly, the metric could be evaluated over an entire company. At this level, the comparison could be to determine the consistency of information over the entire

company or compare with other companies. A summary of the common generalizations that could be completed is shown in Figure 25.

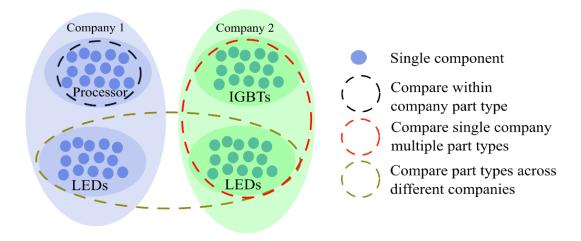


Figure 25: Summary of comparison methods for generalizing metric values

In most cases it is not feasible to find all information and evaluate the metrics for all parts within a manufacturer or even subcategory within the manufacturer. A method to solve this problem is to select a subset of parts from the category or manufacturer and determine the metric value for each part. Then, statistical analysis can be completed on the dataset of metric values such as determining the mean, standard deviation, minimum, and maximum values. This information can be used to make comparisons and judgements between parts from a manufacturer or compare different manufacturers.

An alternative method that will become more feasible in the coming years is the web scraping of information. When detailed part information pages in the same format are provided for each part by a manufacturer the need for manual reading and interpretation can be removed and automated. A script is developed to read and store the information that is available for each part and then the same statistical analysis can be completed. The current pitfalls with this method include requiring the same .html format for parts to work properly and that not all datasheet information or parameters are included in the part information pages. There is a trend towards more information being readily available but the .pdf datasheet is still the dominant method of sharing information.

Verifying and Adjusting Multiplier Level Values

The metric multiplier values provided in the above tables for both TIA and MIA were determined through discussions and analysis of datasheets and other available information for parts. Continued discussions were completed to change the number of levels and values for each multiplier. Depending on the user of the metrics, the levels may be adjusted for specific interests and intended uses. For example, a user interested in gathering information for a large group of parts may want to apply a heavier penalty when information is not available on the part information page. An application with high ambient temperatures may put higher focus on the ratings multiplier within TIA. Adjustment of these values can be completed through discussions amongst peers from varied backgrounds (such as with the development of an FMEA), through an online survey from interested parties, or based off of the results of reliability assessments.

The verification of the metric multiplier values can be completed ideally through a large-scale analysis of parts across many different manufacturers and types of parts. By determining the multiplier values for each part, the percentage of the total

part set with each specific level can be used as a method of verification. The multiplier level values would now represent the percentage of parts that met the required conditions. For example, if 10% of parts provided both a thermal resistance and power dissipation value, the TIA conversions multiplier could be set to 0.9 as a reflection of the 10% with the best level of information. The percentage of parts with each subsequently lower multiplier level would then be used to determine the remaining metric levels. In a less quantitative fashion, verification of the values can be completed through comparing the averaged metric final values for manufacturers and evaluating if the hierarchy of those values matches the expectations of companies in the industry.

Case Study Analysis

To evaluate the available information and determine the common combinations of metric values, a list of parts was analyzed. All parts are COTS devices to be used in a more demanding application. A wide range of part types from different manufacturers have been provided and are shown in Table 22.

Table 22: List of parts for case study analysis

Part ID Number	Manufacturer	Part Description	Part ID Number	Manufacturer	Part Description
1	Abracon	MEMS oscillator	12	Micron	Multi-chip memory
2	Aptina	Active pixel sensor	13	Rohm	Zener diode
3		Current sense amplifier	14		8-bit microcontroller
4	Diodes Inc.	Zener diode	15	Silicon Labs	8-bit microcontroller
5		Hall effect sensor	16	ST Micro	6-axis IMU
6		Pre-biased transistor array	17	Texas Instruments	Linear regulator

7		Schottky diode	18		Mobile processor
8		DC/DC converter	19		Temperature sensor
9	T Tr 1.	DC/DC converter	20		RS485 transceiver
10	Linear Tech	Current sense amplifier	21		CAN transceiver
11		DC/DC converter	22	Vishay	Zener diode

All available information was gathered for each of the 22 parts. Using this information, comparisons of the manufacturer's and part's information availability across many categories such as thermal information, material information, and reliability modeling required information. This information is used to draw conclusions about the information availability for part types and manufacturers and will be incorporated into reliability estimations. This list of parts should not be considered as representative for all electronic parts. These parts have already been selected for consideration in a space application and thus may have more information provided than the typical part. The parts are organized into the following part types:

Table 23: Part numbers with associated categories

Category	Transistors	Sensors	Amplifiers	Diodes	Converters / Transceivers	Processors
Part ID Numbers	1, 6	2, 5, 16, 20	3, 10	4, 7, 13, 22	8, 9, 11 17, 20, 21	12, 14, 15, 18

Thermal information is the first key information area that was analyzed. For each of the parts, the datasheet parameters for all temperature ratings and thermal information was gathered to incorporate into the reliability estimations and determine the TIA values. Table 24 shows a summary of the information collected for each of the

parts. An operating temperature range was found for all parts and power dissipation / thermal resistance information was provided sporadically. One interesting finding is that of the 10 parts that provided junction operating temperature ranges, 9 provided thermal resistance values. Alternatively, only 2 of the 9 parts that used ambient operating temperature ratings provided thermal resistance values.

Table 24: Thermal information collected for parts

Pat ID Num.	Category	Min Op. Temp	Max Op. Temp	Temp. Location	Power Diss. Provided?	R_t Provided?
1	Sensors	-30	70	Ambient	*	
2	Amplifiers	-40	85	Ambient	*	
3	Converters / Transceivers	-40	85	Ambient		*
4	Processors	-25	85	Operating		
5	Sensors	-40	85	Ambient		
6	Processors	-40	85	Ambient	*	*
7	Transistors	-40	105	Ambient		
8	Converters / Transceivers	-40	125	Junction		*
9	Converters / Transceivers	-40	125	Junction		*
10	Processors	-55	125	Ambient		
11	Converters / Transceivers	-40	125	Junction		*
12	Converters / Transceivers	-40	125	Ambient	*	*
13	Converters / Transceivers	-55	125	Ambient	*	
14	Processors	-55	135	Ambient		
15	Diodes	-65	150	Junction	*	*
16	Sensors	-40	150	Ambient	*	
17	Transistors	-55	150	Junction	*	*
18	Diodes	-55	150	Junction		*
19	Amplifiers	-55	150	Junction		*
20	Diodes		150	Junction	*	
21	Sensors	-55	150	Junction		*
22	Diodes	-55	150	Junction		*

Figure 26 shows the minimum and maximum temperature operating temperature rating values provided for each part and are color sorted by the category of part per Table 23. It is important to note that the values are directly from the part datasheets and have not been converted to account for distinct locations of measurement (such as ambient vs. junction). Additionally, jitter has been applied to the points to avoid direct overlap of points and every part's rating is represented by the intersection of lines on the plot.

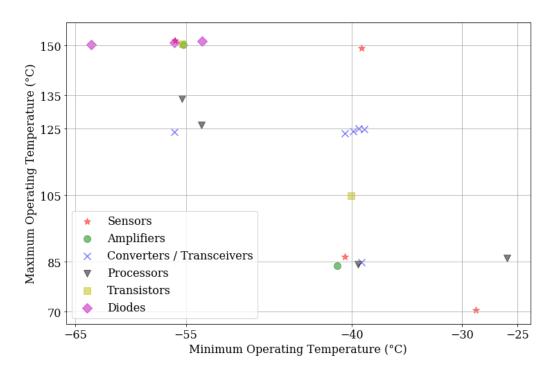


Figure 26: Comparison of minimum and maximum operating temperature values for each part

There is no direct relationship between the type of parts and the operating temperature ratings that are seen. Interestingly, the sensors group of products provided the widest variance in rating values and the converters / transceivers group provided

the most consistent rating values. All of the diodes analyzed provided a maximum temperature value of 150 °C (all also used a junction temperature location). The most common temperature rating was found to be (-55 °C, 150 °C) and made up of 23% of the total population of parts. The most limiting parts were found to only have a maximum temperature of 70 °C and a minimum temperature of -25 °C. Using this information, the three different multiplier factors for the TIA metric were determined (conversions, ratings, location). A comparison plot of the ratings and conversions multiplier factors is in Figure 27. Both multipliers are between 0 and 1 but only the regions where data points were found have been plotted.

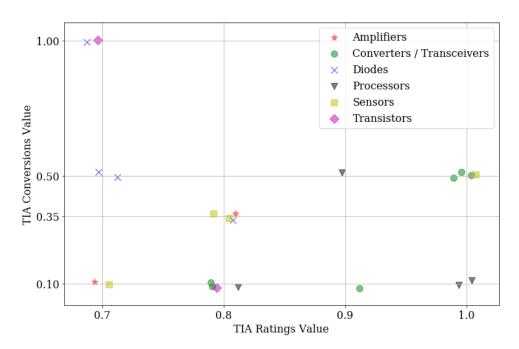


Figure 27: Part TIA rating value and TIA conversion value for the sample part list

Figure 27 shows that none of the parts have a combination of high conversion and rating TIA multiplier levels. Parts that provide a high conversion value are much more likely to provide a lower number and quality of temperature ratings. Only 2 parts

provided enough information to receive the highest conversions level, and both of those provided the lowest information in terms of ratings of all the sampled parts. The same is seen for high ratings values which are less likely to provide conversion information. Not shown in the figure, 21 of the 22 parts provided a specific location for their absolute maximum rating and received a high value for the location multiplier aspect of TIA. Using these values, the final TIA metric value can be determined (see Figure 28).

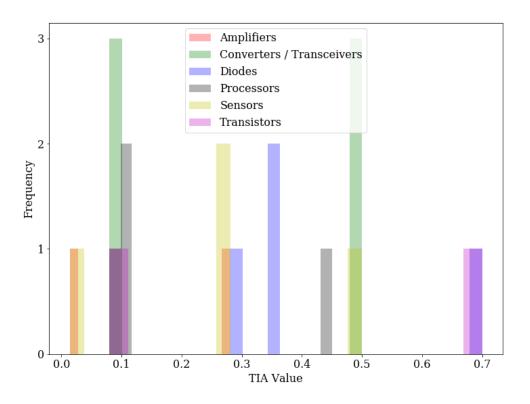


Figure 28: Final TIA Value for different categories of parts

There is a wide range in final TIA values and again no specific trends based on types of parts. Diodes provided the highest average value TIA value at 0.42. The diode's parts also had the highest maximum value and the highest minimum value. The

amplifiers provided the lowest average value of 0.147. A summary of the mean, minimum, and maximum values is provided in Table 25.

The material information for each part was also collected. Using this information, the MIA multipliers were determined with the results shown in Figure 29. Five of the 22 parts did not provide tabular or IPC 1752 information. The most common combination of multiplier level values was 0.8 for access (the information is provided online but not on the part information page) and 0.9 for content (tabular information but not the official IPC 1752 documentation). Unlike with the multipliers in TIA, as a higher access value is found for a part, it is likely that a high content value will be found. Using this information, the final MIA values can be determined. The statistical analysis on the groups for MIA is shown in Table 25.

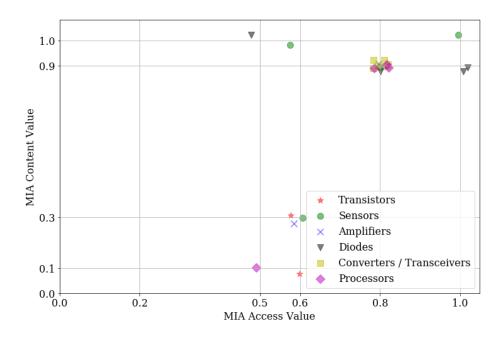


Figure 29: Comparison of MIA content and access multiplier values for each part

Table 25: Statistical analysis of part category TIA and MIA values. Highlighted red and green values are lowest and highest mean values subsequently.

	Temperature Information Availability			Material Information Availability		
Part Category (Count)	Mean Value	Min Value	Max Value	Mean Value	Min Value	Max Value
Amplifiers (2)	0.147	0.014	0.28	0.86	0.72	1.00
Converters / Transceivers (6)	0.292	0.080	0.50	0.518	0.05	0.72
Diodes (4)	0.42	0.280	0.70	0.665	0.50	0.72
Processors (4)	0.183	0.080	0.45	0.63	0.18	0.90
Sensors (4)	0.269	0.014	0.50	0.39	0.06	0.72
Transistors (2)	0.39	0.080	0.70	0.81	0.72	0.90

The amplifier category of parts provided the highest average MIA value and one of the amplifier parts provided the highest possible value of 1. The sensors category provided the lowest average value of only 0.39. A plot comparing the TIA and MIA values for each part is shown in Figure 30. Generally, parts that have a higher TIA value will also have a higher MIA value. The converse of this is not true, as parts with high MIA values can have high or low TIA values. The diodes category of parts provided the most combined thermal and material information compared with the other groups.

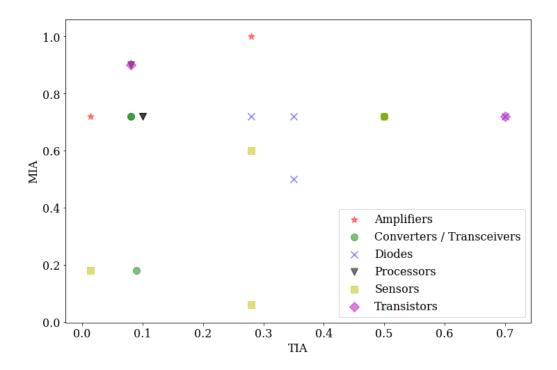


Figure 30: Comparison of MIA and TIA values for each part

Based off the TIA and MIA values for each part, the similarity between the parts can be determined. The Euclidian distance similarity was completed between the parts from the same category and shown in Figure 31. The comparison value between any two parts from the same category is the intersection of the two parts on the x and y axis. With Euclidian distance, darker colors are closer to 0 and represent parts that are more similar. In the case where the same part is compared with itself (along the diagonal of the diagram in Figure 31) the distance is 0. The processors category provided the most similar level of information while the transceivers category provided different levels of information.

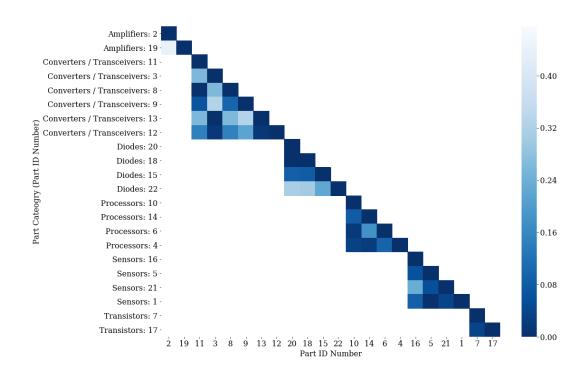


Figure 31: Euclidian distance similarity between parts based on TIA and MIA value (higher numbers are less similar)

Statistical analysis was also completed based on manufacturers. This can be used for determining the consistency of information from a single manufacturer across multiple types of parts. The results from the analysis are shown in Table 26. For thermal information, Texas Instruments provided the highest mean value of 0.49 (over 5 parts). Abracon and Micron both provided the highest material information value of 0.90. One processor provided by ST Micro provided the lowest TIA and MIA values. This does not mean that ST Micro in general provides low information, just that the one sample in this case study did not provide elevated levels of information. As discussed in the metrics section, the generalization of these values for a manufacturer requires a large

enough sample size to accurately capture the scope of products provided by the manufacturer.

Table 26: Statistical analysis of MIA and TIA values for different manufacturers

	Temperature Information Availability			Material Information Availability		
Manufacturer (Count)	Mean Value			Mean Value	Min Value	Max Value
Abracon (1)	0.080	0.080	0.080	0.900	0.90	0.90
Aptina (1)	0.280	0.280	0.280	0.060	0.06	0.06
Diodes Inc (5)	0.462	0.280	0.700	0.752	0.60	1.00
Linear Tech (4)	0.066	0.014	0.090	0.585	0.18	0.72
Micron (1)	0.080	0.080	0.080	0.900	0.90	0.90
Rohm (1)	0.280	0.280	0.280	0.720	0.72	0.72
ST Micro (1)	0.014	0.014	0.014	0.180	0.18	0.18
Silicon Labs (2)	0.100	0.100	0.100	0.720	0.72	0.72
Texas Instruments (5)	0.490	0.450	0.500	0.478	0.05	0.72
Vishay (1)	0.350	0.350	0.350	0.500	0.50	0.50

As an example, the comparison of the information for each part from Texas Instruments is shown in Figure 32. From the case study list there were 3 transceivers, 1 processor, and 1 sensor from Texas Instruments. The three transceivers did not have similar levels of information provided. The information available from the sensor was comparable with the processor and one of the transceivers. For comparing a manufacturer, the ideal case would be the same level of (high) information for all parts and thus low Euclidian distance.

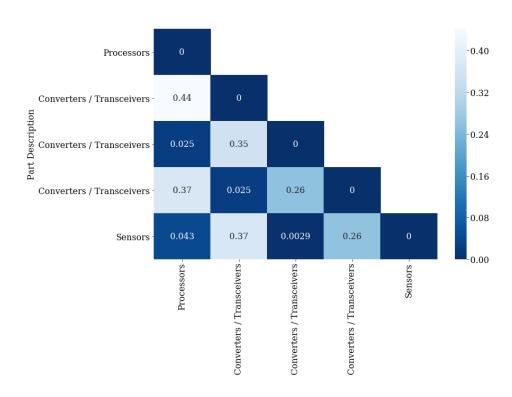


Figure 32: Euclidian distance similarity between Texas Instruments parts (higher numbers are less similar)

Chapter 5: Software Implementation and Analysis

Combining the part information databases, application condition collection and approximation methods, and information availability metrics, a time to failure distribution is determined. Figure 33 shows the overall implementation encompassing the sources of information that impact the final time to failure distribution (blue circles) and *hyper* parameters that must be selected based on the type of analysis and engineering judgement (red text), like the kernel bandwidth levels for each application condition input and the q value that controls the severity of the thermal information availability (TIA) on the time to failure distribution.

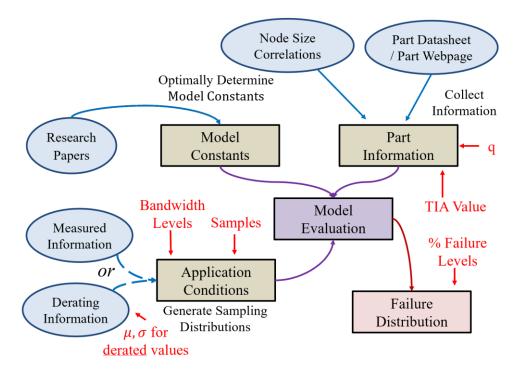


Figure 33: Software Implementation flowchart with information sources (blue circles) and hyper parameter (red text).

A Monte-Carlo Sampling method is used to determine the final time to failure distribution. Distributions are approximated for each input and many samples (n) are drawn from each to determine a time to failure distribution. The final distribution (T(t))can then be analyzed based on application requirements and reliability goals. For example, the time to a certain X percentage of failures is simply the distribution value at which X percent of the samples have failed. This is also equivalent to the probability that a part will fail (i.e. a part has a 1% chance to fail is equivalent to the probability that 1 part will fail if 100 are in a population). Additionally, the probability that a part will fail by a certain period is equivalent to the percentage of samples at the specified time in the time to failure distribution. Figure 34 shows a sample distribution generated with a noisy normal distribution and is analyzed with commonly used practices. The green dashed line is the mean time to failure (50% of the samples have failed), the orang dashed line shows that there is a 16% probability that a part will fail at or before 8 years, and the red dashed line shows that a part will have a 90% chance of failure will occur at 12.5 years.

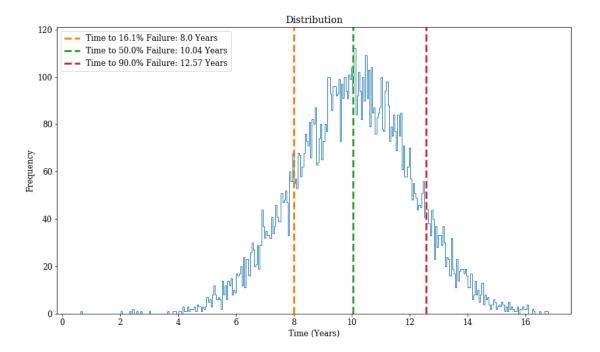


Figure 34: Sample time to failure distribution (simulated data) showing analysis of time to certain percentage of failures (red line) and the probability of failure for a certain length of time (orange dashed line).

This methodology can be used in a number of ways to compare parts across different application environments and reliability expectations. Primarily, the methodology gives a time to failure distribution based on specific part parameters and application conditions. It can also be used to evaluate the impact that changes in part parameters or application conditions will have on the failure distribution. This means that completing comparisons of differently rated or designed parts (such as a commercial part compared to a military grade part), or different environments can be completed to determine potential impact. Using the thermal information availability metric, the methodology can also evaluate the impact on the failure distribution that

different levels of information uncertainty has. Examples with each of these cases are presented in the sections below.

Single Part Reliability Estimation

Part reliability was approximated with the following part and model constant parameters (see Table 27) for the TDDB failure mechanism model. In this case, the part parameters and model constants were treated as point estimates (not distributions) to show the impact that the application conditions have on the time to failure distribution.

Table 27: Sample Part Part Parameters and Model Constants

Parameter	Unit	Value
Oxide Thickness	nm	2
Maximum Power Dissipation	mW	0.7
Thermal Resistance	°C/W	5
Node Size	nm	35
A0 Model Constant	N/A	2.25E+03*
Gamma Model Constant	N/A	2.33*
Activation Energy	eV	0.4

Application information was simulated for gate voltage, temperature, drain source voltage, and drain source current values using noisy normal distributions. The resulting time series data, which serve as the inputs for the analysis, are shown in Figure 35. Using this data, the output samples are generated using the time series data distribution approximation method detailed in Chapter 3. An example comparison

input and output distribution of temperature values is shown in Figure 36 where 5000 output samples are sampled.

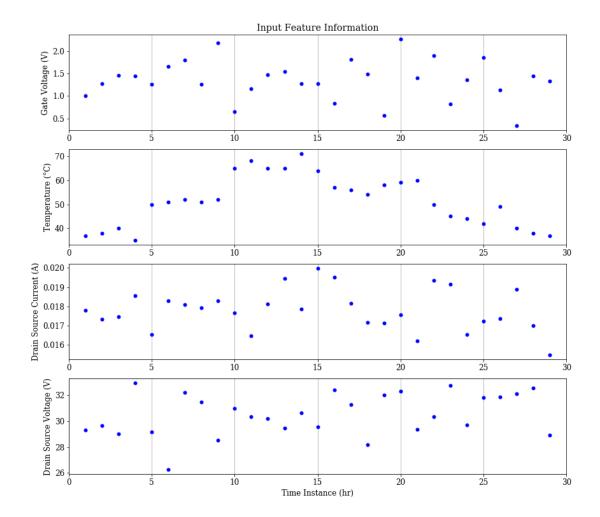


Figure 35: Simulated application condition information for TDDB mechanism model parameters.

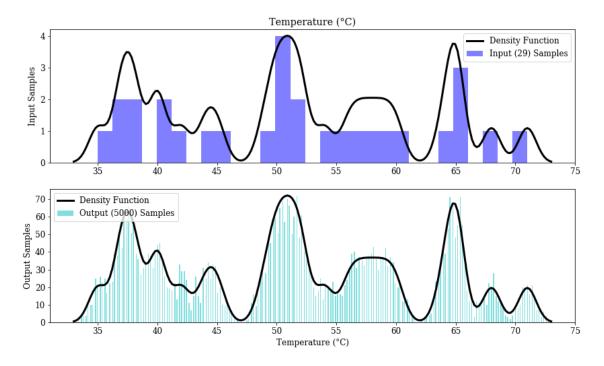


Figure 36: Comparison of input and output samples using kernel density distribution approximation method. The top plot shows the input samples and the kernel density that was approximated (black line). The bottom plot shows the final samples generated using the kernel density distribution.

Using this simulated information and selected part parameters modeling constants, the time to failure can be calculated for each sample and thus a distribution of time to failure is determined. In this case, the modeling constants and part parameters are held constant to evaluate the impact that the application condition distributions have on the failure distribution. This distribution is shown in Figure 37.

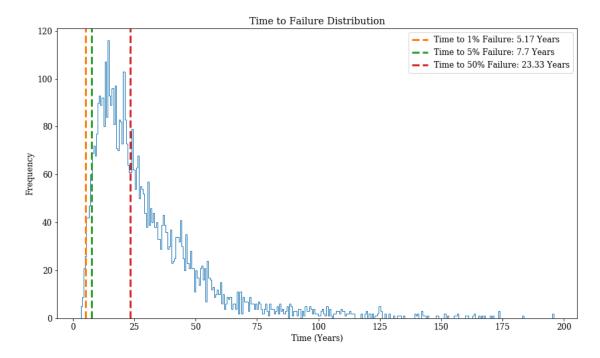


Figure 37: Time to failure distribution for a single part generated from 5000 samples from application condition distributions. Dashed lines show the time at which 1%, 5%, and 50% of all samples will fail.

Comparison of Failure Distribution with Different Part Parameter

One common comparison is between similar parts with a different feature or parameter. For example, when transferring to a new generation of part with a smaller node size, geometric features about the part will change which can impact reliability. This is exemplified by the example below where the oxide thickness layer parameter is changed between 1 and 2 nm. All other factors (application conditions, model constants, other part parameters) are unchanged from the first example. Using this information and 5000 samples, both TDDB time to failure distributions are shown in Figure 38 and the time to X% failures are shown in Table 28. The results show that by

halving the oxide thickness, the time to failure is drastically reduced, with the mean time to failure reduced 5-fold.

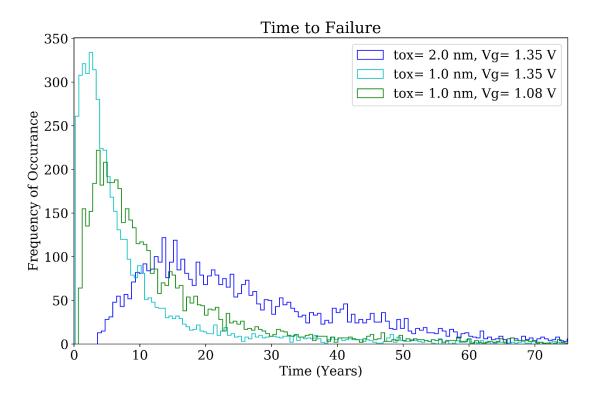


Figure 38: Projected TDDB time to failure for different oxide thicknesses (all other inputs remained constant). Gate voltage of 1.08 determined by using relationships between oxide thickness, node size, and gate voltage (see Chapter 3).

Table 28: Time to X% Failure for Different Oxide Thickness (all other inputs held constant)

	Time to Failure (Years)						
Percent Failure	$t_{ox} = 2.0 \text{ nm}$ $V_g = 1.35 \text{ V}$	t_{ox} = 1.0 nm V_g = 1.08 V*	t_{ox} = 1.0 nm V_g = 1.35 V				
1 %	5.25	1.15	0.41				
5 %	7.87	1.88	0.73				
10 %	9.94	2.82	1.15				
25 %	14.64	4.93	2.41				
50 %	23.35	9.02	4.74				

Comparison of Different Temperature Distribution Approximation Methods

To compare the accuracy of application condition approximation methods, the temperature of a computer CPU (i7-8550U) was monitored for 24 minutes during normal usage (browsing the web, watching videos, programming). Data was collected using the RealTemp program and temperature was collected each second. This represents the time series collection approximation method. By comparison, the maximum junction temperature for the processor is 100 °C [75]. Figure 39 shows a comparison of the results from the data collection and references the maximum junction temperature.

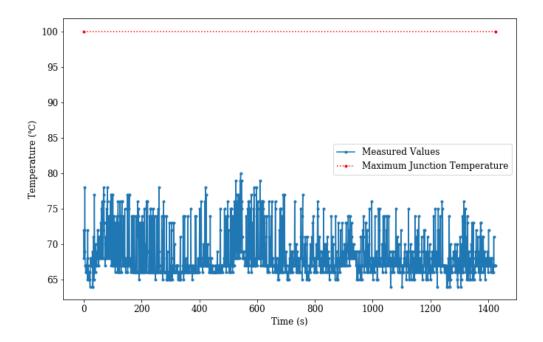


Figure 39: Comparison of collected temperature information and processor maximum junction temperature.

Using this information, the kernel distribution for the sensor collected data was determined and is plotted in Figure 40. An assumed normal distribution was also

created to represent the application based on the maximum junction temperature. The distribution is made up of the same number of samples (1440 points) with a mean value of 85 °C and standard deviation of 5 °C (see red line in Figure 40). Using these distributions, 5000 output samples are drawn and used to form the time to failure distributions which are plotted in Figure 41. The junction failure distribution uses a constant value of 100 for each sample. The results show that without using a distribution to approximate the application, the time to failure distribution is drastically reduced. Even when an assumed junction distribution which remains below the maximum value is selected, the time to failure distribution projects failure in half the amount of time of the measured value distribution. This is seen more clearly in

Table 29 which shows the time to X% failure for each of the failure distributions.

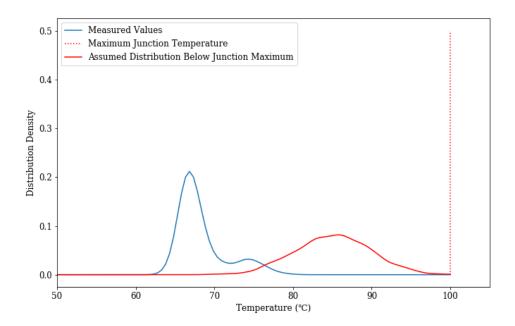


Figure 40: Comparison of measured values kernel approximation distribution, assumed normal distribution below the maximum junction temperature, and the maximum junction temperature.

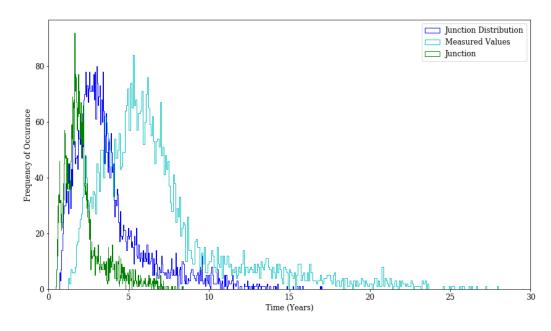


Figure 41: Comparison of TDDB time to failure distribution for different temperature distribution approximation methods. The Junction distribution was determined by using a constant value of 100 °C for all samples.

Table 29: Comparison of Time to X% Failure for Different Temperature Distribution

Approximation Methods

_		Time to Failure (Years)						
Percent Failure	Measured Values	Junction Distribution	Junction (Constant Value)					
1 %	1.82	0.91	0.59					
5 %	2.34	1.22	0.74					
10 %	2.98	1.54	0.96					
25 %	4.22	2.2	1.37					
50 %	5.85	3.11	1.84					
75 %	7.85	4.31	2.42					
90 %	12.85	6.78	3.98					
95 %	15.97	8.65	5.03					
99 %	21.68	12.22	6.62					

Using the thermal information metric developed in Chapter 4, a comparison can be completed. In this case, the same parameters as with the first example in Chapter 5 are used but with different TIA values. The two values selected are 0.1 and 1, representing the cases where minimal and maximum thermal information are provided. Higher TIA values lead to lower uncertainty in the thermal resistance parameter. A q value of 10 was selected, meaning that the impact of the TIA value on the thermal resistance standard deviation is divided by 10. The results of this analysis are shown in Figure 42. The distributions themselves are similar, but the low TIA value corresponds with a wider overall distribution. The time to X% failures are shown in Table 30.

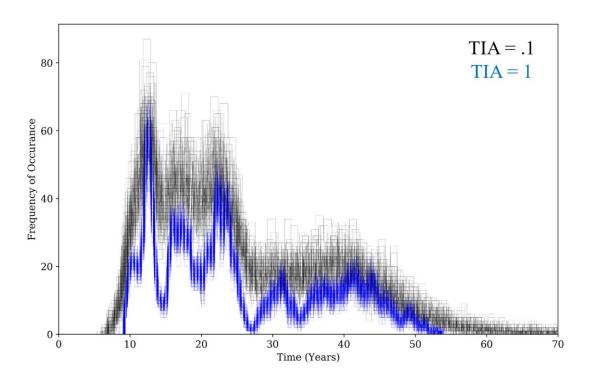


Figure 42: TIA Comparison Failure Distributions

Table 30: TIA Comparison Percentage Failure Time to Failure Distribution

Percent Failure	TIA	= 0.1	TIA = 1.0	
reicent ranuie	Mean	STD	Mean	STD
1 %	9.72	0.88	8.89	0.24
5 %	11.00	0.60	10.62	0.14
10 %	12.23	0.23	11.89	0.12
25 %	16.04	0.90	15.58	0.15
50 %	22.66	2.75	22.35	0.16

Evaluation of Different Sample Sizes

Another important attribute that is selected is the number of samples that are drawn frm each input distribution and make up the final time to failure distribution. Intuitively, the more samples drawn from each distribution, the more accurately the underlying distributions are represented and thus a more accurate estimation on the time to failure. The impact of different *output* samples was evaluated for 5 different levels using the same part parameters and application condition information. The resulting distributions are shown in Figure 43. In this case, a kernel density method was used to generate a distribution instead of a histogram result in order to better visualize the data. Table 31 shows the time to X% failure for each sample size value.

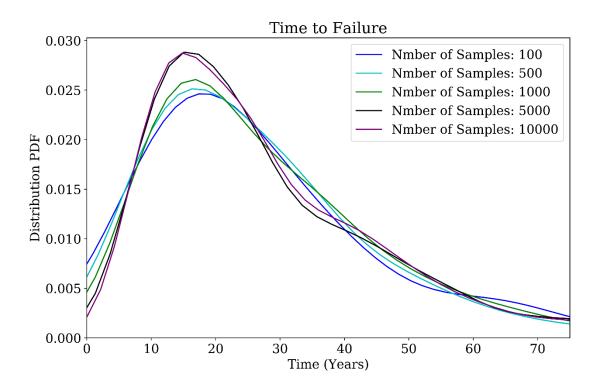


Figure 43: Comparison of different sample sizes on failure distribution

Table 31: Time to X% Failure for Different Output Sample Sizes

	Time to Failure (Years) Based on Distribution Sample Size						
Percent Failure	100	500	1000	5000	10000		
1 %	6.25	5.85	5.4	4.86	4.91		
5 %	8.87	7.42	7.89	7.65	7.64		
10 %	9.94	9.48	10.03	9.96	9.93		
25 %	14.85	13.96	14.97	14.6	14.66		
50 %	23.31	23.39	23.98	23.4	23.99		

Chapter 6: Contributions and Future Work

This thesis has developed an information-based reliability assessment to incorporate sources of uncertainty in part parameters, application conditions, and model constants into projections for die-level semiconductor wearout mechanisms. This included determining the sources of information which are available for commercial off the shelf (COTS) devices and can be used for reliability projections. This is also compared with the information that is provided for non-COTS devices (military, space, automotive grade parts).

The availability of thermal and material information of individual parts is quantified using metrics and can be incorporated into the time to failure projections. Methods have been developed to generalize metric values and draw comparisons between parts. Trends in information availability were analyzed and determined using a case study of COTS parts.

Additionally, numerous methods have been developed to approximate application condition and part parameter distributions. This includes a method of converting sensor collected application information into a distribution which can be sampled from and a process of using node or feature size information to select geometric part parameters. These methods are fully integrated into the reliability estimation methodology. Using this system, comparisons between different components, applications, and levels of information availability can be analyzed.

Future implementations can expand the list of failure mechanisms beyond what is discussed in this thesis. The same principles of modeling application conditions and part parameters apply to all failure models. Additionally, large scale data gathering methods can be used to mass collect information about parameters. This will lead to better defined correlations between part parameters and standardized metric values based on the type of component and manufacturer. These metrics can be further integrated into the reliability methodology and parameter values can be optimized using known time to failure data. There are also many unique situations and considerations that have not been considered in this thesis. This includes cases where a COTS component is purchased by a third party, tested and qualified to a higher-level part rating, and then refinished to represent this change. This additional information must be provided and analyzed accordingly.

Evaluating an comparing the validity of information provided for different rating parts is another area where improvements can be made. Understanding if the provided information is accurate has predominately been assumed in this thesis but is not necessarily true. Through physical testing of different parts in comparison with part specifications, the validity of the information can be completed.

Appendices

Appendix A: Time to Failure Distribution Python Code

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.neighbors import KernelDensity
import openpyxl
import matplotlib
def inputExtracter(samples,samplesName,numOutputs,kernelBandwidth = 0.5,extraSpace = 2,figureSize =
(14,8),plot=True):
  This function determines an approximate kernel function around an input data space and determines a certain
number
  of output points based on the fit distribution.
  *Variables*:
  samples: Inputs
  samplesName: Identifyer for the samples (will show on produced plots)
  numOutputs: Number of final data points to make
  sampleRange = np.linspace(min(samples) - extraSpace,max(samples) + extraSpace, 200)
  kde = KernelDensity(bandwidth=kernelBandwidth,kernel='gaussian').fit(samples)
  prediction = np.exp(kde.score_samples(sampleRange.reshape(-1,1)))
  comps = pd.DataFrame()
  comps['sampleRange'] = sampleRange
  comps['Prob'] = prediction
  comps['ProbCuma'] = np.cumsum(comps.Prob) / sum(comps.Prob)
  testPoints = np.random.rand(numOutputs)
  vals = [comps.sampleRange[comps[comps.ProbCuma > i].index[0]] for i in testPoints]
  if plot == True:
    plt.figure(figsize=figureSize)
    plt.subplot(2,1,1)
    plt.title(samplesName)
    labelString = "Input (" + str(len(samples)) + ") Samples"
    numBins = round(len(samples) / 1)
    plt.hist(samples,numBins,faceColor='b',alpha=.5,label=labelString)
    plt.plot(sampleRange[:,None],max(np.histogram(samples,numBins)[0]) / max(comps.Prob)*prediction,
          "k-",lw=3,label = "Density Function")
    plt.ylabel("Input Samples")
    plt.legend()
    plt.subplot(2,1,2)
    labelString = "Output (" + str(numOutputs) + ") Samples"
    numBins = round(numOutputs / 10)
    plt.hist(vals,numBins,faceColor='c',alpha=.5,label = labelString)
    plt.plot(sampleRange[:,None],max(np.histogram(vals,numBins)[0]) / max(comps.Prob)*prediction,
          "k-",lw=3,label="Density Function")
    plt.ylabel("Output Samples")
    plt.legend()
    plt.xlabel(samplesName)
  return vals, kde
```

```
def TDDB(gamma, T, Vt, tox, Ea, A=1, k=8.617e-5):
  """Determines the estimated time to failure for the time dependent dielectric breakdown E model method.
  The application conditions of T and Vt should be supplied as arrays of information whereas the other inputs
  should be single inputs."""
  estimate = A*np.exp(-gamma*np.array(Vt) / tox)*np.exp(Ea / (k*np.array(T)))
  return estimate
def stringChecker(target, string):
  """Determines if a target is located within a strnig. Function is used to grab the information using only general
terms.""
  correct = [s for s in string if target in s]
  if len(correct) == 1:
    return correct[0]
    return value
  if len(correct) > 1:
    print("Please refine target (Mulitple Options: ")
     print(correct)
  if len(correct) == 0:
     print("No string found")
def conditionPlotter(infoFrame,titleString = 'Input Feature Information',figWidth=14,figHeight=5):
  time = infoFrame.columns.tolist()[0]
  features = infoFrame.columns.tolist()[1:]
  plt.figure(figsize=(figWidth,figHeight*len(features)))
  font = {'family': 'serif',
       'weight': 'normal',
       'size' : 12}
  matplotlib.rc('font', **font)
  for i,feature in enumerate(features):
     plt.subplot(len(features)+1,1,i+1)
     if i == 0:
       plt.title(titleString)
     plt.plot(infoFrame[time],
          infoFrame[feature],'bo',markersize=5)
     plt.ylabel(feature)
    plt.grid(axis='x')
    plt.xlim(0,len(infoFrame[features[0]])+1)
  plt.xlabel(time)
def failurePlotter(failureDistribution,pcts,figSize = (14,8),stringTitle='Time to Failure Distribution'):
  sortedFails = np.sort(failureDistribution)
  failTable = [round(sortedFails[int(round(i / 100*len(failureDistribution)))],2) for i in pcts]
  ft = pd.DataFrame()
  ft['Percent'] = pcts
  ft['TTF'] = failTable
  plt.figure(figsize=figSize)
  numBins = int(numOutputs / 15)
  plt.ylim(0,max(np.histogram(timeFail,numBins)[0])+5)
  plt.title(stringTitle)
  plt.hist(failureDistribution,bins=numBins,histtype='step')
  for row in range(len(pcts)):
     pctString = Time to '+str(ft.Percent[row]) + "% Failure: "+str(round(ft.TTF[row],2)) + 'Years'
    plt.plot([ft.TTF[row],ft.TTF[row]],[0,max(np.histogram(timeFail,numBins)[0])+5],'--',lw=3,label=pctString,)
  plt.ylabel('Frequency')
  plt.xlabel('Time (Years)')
```

```
plt.legend()
  return ft
def uncertaintyAdder(conditionInformation,targetStrings,stdLevel):
  for i,value in enumerate(targetStrings):
    original = conditionInformation[stringChecker(value,conditionInformation.columns.tolist())]
    updated = original + np.random.normal(0,stdLevel[i],len(original))
    conditionInformation[stringChecker(value,conditionInformation.columns.tolist())] = updated
def ThermalResistanceTIA(TIA,mean,samples,q=100,enable=True):
  if enable == True:
    beta = mean / q * (1-TIA)
    newThermals = np.random.normal(mean,beta,samples)
    return newThermals
failureMechanisms = ['TDDB','HCI','EMI','NTBI','Corrosion']
mechanismAspects = [5,5,6,4,5]
mechanismPartParams = [6,5,6,8,7]
mechanismParams = \{\}
for i,mech in enumerate(failureMechanisms):
  mechanismParams[mech] = [mechanismAspects[i],mechanismPartParams[i]]
mechanismParams
selectedMech = 'TDDB'
numPartParams = mechanismParams[selectedMech][1]
startPointPart = 6
endPointPart = startPointPart + numPartParams
numberAspects = mechanismParams[selectedMech][0]
numOutputs = 5000
targetStrings = ['Source Voltage','Source Current']
uncertaintySTDLevels = [.1,.1]
bandWidthLevels = [.1,.75,.001,.1]
percentLevels = [1,5,50]
TIA = 1
qVal = .1
numConditionSamples = 32
# Importing Information
bk = openpyxl.load_workbook("TDDB Template.xlsx")
sheetNames = bk.sheetnames
sheet1 = bk[sheetNames[0]]
partUnits = []
partParamNames = []
partValues = []
# Grab parameter information (left side of excel sheet)
partParams = sheet1['A' + str(startPointPart):'C' + str(endPointPart)]
for parameterRow in partParams:
```

```
partParamNames.append(parameterRow[0].value)
  partUnits.append(parameterRow[1].value)
  partValues.append(parameterRow[2].value)
partInfo = pd.DataFrame()
partInfo["Parameter"] = partParamNames
partInfo["Unit"] = partUnits
partInfo["Value"] = partValues
# Create dictionary of information for future reference / use
info = \{\}
for row in range(len(partInfo)):
  info[partInfo.Parameter[row]] = partInfo.Value[row]
# Grab information of the condition information (Need to supply starting and ending columns for feature info)
conditionNames = []
conditionUnits = []
conditionValues = []
for col in sheet1.iter_cols(min_col = 5,max_col=4+numberAspects,min_row=5):
  conditionNames.append(col[0].value)
  conditionUnits.append(col[1].value)
  colVals = []
  for cell in range(2,numConditionSamples-1):
    colVals.append(col[cell].value)
  conditionValues.append(colVals)
condStrings = []
for name in range(len(conditionNames)):
  condStrings.append(conditionNames[name] + " (" + conditionUnits[name] + ")") \\
# Create information dataframe for future reference / table
conditionInfo = pd.DataFrame(np.matrix(conditionValues).T,columns=condStrings)
# Inject uncertainty in some features if they have uniform values / only 1 value provided.
uncertaintyAdder(conditionInfo,targetStrings,stdLevel = uncertaintySTDLevels)
# Split time feature off of other condition information for plotting / analysis
time = conditionInfo.columns.tolist()[0]
features = conditionInfo.columns.tolist()[1:]
# Number of samples to use for the analysis
information = []
outputSamples = []
models = []
# Plot the input conditions (after uncertainty is added)
conditionPlotter(conditionInfo,figHeight=4)
plt.savefig('Input Features.png')
# Transform the input feature information into distribution and sample from those to form the new samples
for i,feature in enumerate(features):
  information.append(inputExtracter(np.array(conditionInfo[feature]).reshape(-1,1),feature,
                       numOutputs=numOutputs,kernelBandwidth = bandWidthLevels[i],plot=True))
  outputSamples.append(information[i][0])
```

```
models.append(information[i][1])
  plt.savefig(feature + ' Distribution Plot.png')
# Form Dataframe of the new samples
newSamples = pd.DataFrame(np.matrix(outputSamples).T,columns = features)
# Power Dissipation calculation based on voltage and current levels
newSamples[Power (W)'] = newSamples[stringChecker("Source Current",string=newSamples.columns.tolist())] *
newSamples[stringChecker(
  "Source Voltage", string=newSamples.columns.tolist())]
# Convert temp from ambient to junction with power dissipation and thermal resistance
tempA = newSamples[stringChecker("Temp",string=newSamples.columns.tolist())] + 273.15
powerDiss = newSamples['Power (W)']
thermR
ThermalResistanceTIA(TIA,info[stringChecker('Thermal',partInfo.Parameter.tolist())],samples=numOutputs,q=q
Val,enable=True)
tempJ = tempA + powerDiss * thermR / 1000
# Grab the constants and part parameters from the dictionary and use those to make an estimate on TTF using the
model.
tox = info[stringChecker("Oxide",partInfo.Parameter.tolist())]
A = info[stringChecker("A0",partInfo.Parameter.tolist())]
Ea = info[stringChecker("Activation",partInfo.Parameter.tolist())]
gamma = info[stringChecker("Gamma",partInfo.Parameter.tolist())]
Vt = newSamples[stringChecker("Gate Voltage", string = conditionInfo.columns.tolist())]
timeFail = TDDB(gamma,tempJ,np.array(Vt),tox,Ea,A=A) / (365*24*60*60)
# Determine percents of interest and plot the final distribution
failurePlotter(timeFail,pcts = percentLevels)
plt.savefig('Time To Failure Result.png')
```

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