

SEMI M32-0307

GUIDE TO STATISTICAL SPECIFICATIONS

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1 Purpose

1.1 Specifications are based on requirements negotiated between trading partners. This document describes an explicit specification form that defines the risk level as a part of parametric specifications. This approach uses process capability information to focus quality improvement efforts, reduce sampling, and maintain low risks. It is based on the fundamental belief that specifications should facilitate the movement toward processed-in quality instead of inspected-in quality.

1.2 It is important for suppliers and their customers to acknowledge and mutually agree on quality levels so the methods employed will satisfy their expectations. Statistical specifications provide a convenient way to do this.

1.3 Statistical specifications are designed to facilitate the movement toward processed-in quality. They are most appropriate for processes that have been statistically characterized. This means the shape of the statistical distribution that created the product is known, or can be approximated to the satisfaction of the customer and the supplier. It also implies that the statistical control of the process and the measurement systems are defined to the level that is necessary to meet the current needs.

2 Scope

2.1 This guide may be used when changing or adding specifications to the order form aspect of silicon wafer specifications, such as SEMI M1, SEMI M57, SEMI M61, or SEMI M62.

2.2 Statistical specifications apply to all processes that have been statistically characterized. Solutions are given for two product distribution shapes (normal & lognormal), and the advantages of these solutions are explained. Appendix 1 shows the statistically characterized shape for many common silicon wafer processes.

2.3 This guide applies to processes related to the production and use of silicon wafers. It may also be applied to the production and use of other materials.

2.4 This approach implies that the quality level shipped is the same as the quality level produced.

2.5 This methodology can be an effective tool for driving quality improvement.

2.6 This procedure can be coupled with other techniques for centering the mean and reducing the variation within the process distribution as deemed necessary by the customer and supplier.

2.7 Appendix 2 further explains the rationale for this approach.

NOTICE: This standard does not purport to address safety issues, if any, associated with its use. It is the responsibility of the users of this standard to establish appropriate safety and health practices and determine the applicability of regulatory or other limitations prior to use.

3 Limitations

3.1 Outlier effects are beyond the scope of this document.

4 Referenced Standards and Documents

4.1 SEMI Standards

SEMI M1 — Specifications for Polished Monocrystalline Silicon Wafers

SEMI M57 — Guide for Specifying Silicon Annealed Wafers

SEMI M59 — Terminology for Silicon Technology

SEMI M61 — Specification for Silicon Epitaxial Wafers with Buried Layers

SEMI M62 — Specifications for Silicon Epitaxial Wafers

NOTICE: Unless otherwise indicated, all documents cited shall be the latest published versions.

5 Terminology

5.1 Terms and acronyms associated with silicon wafer technology are listed and defined in SEMI M59

6 Examples of Statistical Specifications for Normal Distributions

6.1 The normal distribution is well known. It describes processes that target a specific value and have symmetric random variation about that value. The first portion of the normal statistical specification is the familiar tolerance. It uses an upper specification limit (USL) and a lower specification limit (LSL), or the target plus and/or minus a value. The second portion, after the @ sign below, is a measure of the quality level, in ppm.

LSL to USL @ yy ppm or Target $\pm$ xx @ yy ppm

6.2 Other standard tolerance definitions could be substituted, or other definitions of the quality level such as Cpk, Z-value, or percent could be used.

6.3 Functionally, statistical specifications are similar to conventional tolerances, except that the quality level is stated rather than just implied. Adding the quality level removes the potential for misunderstanding and makes the specification more meaningful.

6.4 Statistical specifications can be directly substituted for tolerances or other forms of specifications. Statistical specifications are especially useful for focusing quality improvement efforts, achieving ship-to-stock relationships, promoting processed in quality, and reducing after the fact inspection. In this environment they could be used as follows:

6.4.1 Through audits and capability reporting a particular parameter is targeted for improvement or chosen as a ship-to-stock candidate.

6.4.2 The control methods, distribution shape, and statistical specification are agreed upon. The tolerance and quality level defined in the statistical specification completely define the needed process capability.

6.4.3 Once it is shown that the required capability is consistently exceeded then reduced inspection sampling can be implemented without increasing the risk to the customer or supplier. In this way the process controls can gradually become the guarantee for quality, and after the fact inspection can be gradually reduced to the level that is needed for outgoing quality reporting.

6.5 *Discussion* — Statistical specifications remove ambiguity, allow small risks, and promote the movement toward better process controls and less after the fact inspection. The quality level (i.e., the yy portion) is often misunderstood. Some people say they want ppm level quality but introduce methods that allow 50,000–200,000 ppm in error. This causes confusion.

6.5.1 Many people have the misconception that tolerances are goal posts that require 100% of the material to fall inside. Processes are usually described by statistical distributions, so specifications have little meaning if a quality level is not defined. For many years, 99.73% (i.e., ± 3 sigma) was considered to be satisfactory. “Within tolerance” was understood to mean within tolerance with a 99.73% confidence, or a 0.27% quality level. Later the 99.73% process was defined as “cruel”. 0.27% was no longer an acceptable quality level, and process drift was understood to cause even higher reject rates. This led to the demand for better process capabilities (i.e., higher Cpk’s), which demanded corresponding improvements in process characterization and control methodologies. At the same time other customers tightened their tolerances to the point that led to over-control. Either extreme can cause a mismatch between expectations and capabilities if the risks are not carefully evaluated.

6.5.2 Capability-based sampling is perhaps the only way to rigorously transfer from inspection-based quality to process control-based quality, without incurring high risks. Statistical specifications create the environment for this to work. Once the specification is clearly defined, it can be clearly achieved. The details of capability based sampling are beyond the scope of this document, but the basic concept is easy to understand. If a process is very capable and controlled, then the system can be relied upon to create the necessary quality level with less after the fact inspection. This is good for both sides. Customers get more reliable quality, and suppliers get the information needed to focus quality improvement efforts and direct resources at the most critical processes.

6.5.3 Once a process has been statistically characterized, everything becomes much easier. Calculations can be done in milliseconds instead of minutes. This includes spec acceptance, comparisons, and many forms of analysis. Multiple levels like % < A, % < B, and % < C are also clearly unnecessary if the distribution shape is known. This prevents a large amount of duplicate work.

7 Examples of Statistical Specifications for Lognormal Distributions

7.1 The lognormal probability function describes many of the one-sided distributions that are encountered in the silicon industry. It applies to those parameters such as flatness and warp that are bounded by zero. For lognormal processes, the value of a parameter could be specified as:

$$\leq xx @ yy \text{ ppm}$$

7.2 Other standard tolerance definitions could be substituted, or other quality level definitions such as ECPK, Z-value, or percent could be used. Again, ECPK is the Equivalent normal Cpk that corrects for non-normality. More information on the Equivalent Cpk is shown in ¶¶.

7.3 As with the normal distribution, adding the quality level removes the potential for misunderstanding and makes the specification more meaningful. The major objectives are to focus quality improvement efforts, achieve ship-to-stock relationships, promote processed in quality, and reduce after the fact inspection. The steps are the same as shown in ¶ 6.4 for the normal distribution. The major difference is that only the upper tail needs to be considered. However, since the lognormal tail goes so much farther out, it might be necessary to accept a less critical quality level.

7.4 *Discussion* — Statistical specifications work very well for processes with lognormal distributions. They have all the benefits described for normal distributions, and in some respects, they are even easier. Since lognormal processes only have one tail, checking each tail to decide which is the most critical is not necessary. Also, it has been empirically observed that lognormal processes are not as prone to mean drifting, so they tend to be more stable. The main hurdle is realizing how much error is introduced if the distribution shape is assumed to be normal when it is not.

7.4.1 Figure 1 illustrates the difference between a lognormal and a normal process. The curve that has a solid line (and is clearly not symmetrical) is the lognormal distribution. The curve with the dashed line is the normal distribution. The error when mistakenly using a normal distribution to characterize a lognormal process is shown in Table 1. For values that increment by 1 sigma from the mean, the ppm greater than that value is given for each curve, and the difference (or error) is calculated. To make it easier to visualize, increments of the simple normal mean and sigma (1.8263 and 0.7568 respectively) are used in the “value” column. For calculating the lognormal statistics the correct lognormal geometric mean of 1.8258 and the lognormal geometric sigma of 0.7550 are used. The error between the curves increases as the point of interest moves toward the center of the distribution, but the most important issue is the length of the tail. The right tail of the lognormal distribution extends along with the histogram, but the normal distribution is much shorter. Visually, the significance might be overlooked in Figure 1, but when the tail probabilities are shown in ppm (see Table 1) the difference is very apparent.

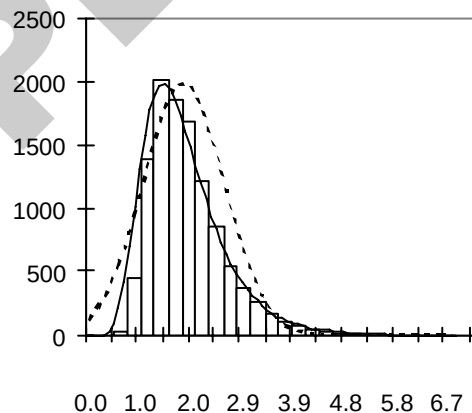


Figure 1
Lognormal vs. Normal Curves

Table 1 Lognormal vs. Normal Data

<i>Value</i>	<i>Value Description</i>	<i>Normal ppm ></i>	<i>Lognormal ppm ></i>	<i>Error</i>
1.8263	mean	500000	420997	79003
2.5831	+1s	158655	141869	16786
3.3399	+2s	22750	42836	20086
4.0967	+3s	1350	12783	11433
4.8535	+4s	32	3914	3882
5.6103	+5s	0.3	1247	1247
6.3671	+6s		415	415
7.1239	+7s		144	144
7.8807	+8s		52	52
8.6375	+9s		20	20
9.3943	+10s		8	8
10.1511	+11s		3	3
10.9079	+12s		1	1

7.4.2 Lognormal distributions can be handled mathematically as easily as normal distributions, if the formulas are known. The difficulty in the past was that many of the calculations developed for the normal distribution were not available for lognormal. The equivalent normal Cpk (ECPK) was developed to address this issue. For the lognormal distribution, ECPK is calculated as shown below. It is an exact mathematical derivation with no estimations or assumptions. It was designed to allow people to see real data and keep all transformations and conversions inside the computer where they are totally invisible. Two cases are presented. ¶ A2-3.3 describes the case where a statistical software package is available, and ¶ A2-3.4 describes a shortcut that may be used when the computation is derived from scratch. In both cases, it is important to remember that only the computer sees these formulas.

7.4.3 Statistical software packages usually output the geometric mean and geometric sigma. If μ is the lognormal geometric mean, σ is the lognormal geo-metric sigma, and $\ln$ is the natural log function, then ECPK is calculated as:

$$ECPK = \frac{\ln(USL) - \ln \left[\frac{\mu^2}{\sqrt{\mu^2 + \sigma^2}} \right]}{3 \left[\sqrt{\ln \left(\frac{\mu^2 + \sigma^2}{\mu^2} \right)} \right]} \quad (1)$$

7.4.3.1 For the example in Figure 1, the lognormal geometric mean is 1.826 and the lognormal geometric sigma is 0.755. If an upper spec limit (USL) of 6 is applied, then the ECPK is 1.06. This is usually done in a computer.

7.4.4 If the computation is programmed from scratch for raw data, it may be convenient to take the natural log of each data point (i.e., do a log transformation) then compute the mean of the transformed data (T_{mean}) and sigma of the transformed data (T_{sigma}). Again, $\ln$ is the natural log function. In this case, the ECPK formula is written as:

$$ECPK = \frac{\ln(USL) - T_{mean}}{3T_{sigma}} \quad (2)$$

7.4.5 The geometric mean and geometric sigma are calculated as follows:

$$G_{mean} = \exp \left[T_{mean} + 0.5T_{sigma}^2 \right]$$

$$G_{sigma} = \left[\left(\exp(2T_{sigma}^2) - 1 \right) \right]^{1/2} \quad (3)$$