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Automotive Package Lead Pullback Elimination Using Monte Carlo Analysis for Determining Leadframe and Blade Design

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Authors' contributions

This work was carried out in collaboration among all authors. Author JST performed the Monte Carlo analysis, did the literature searches and wrote the first draft of the manuscript. Author PACJ managed the actual evaluation, data collection and blade design. Author RAR managed the leadframe and package design. All authors read and approved the final manuscript.

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ABSTRACT

This study focuses on eliminating the lead pullback problem in an automotive quad flat no lead (QFN) package in order to meet the non-negotiable requirement to have a solder wettable or solderable lead sidewall. It involves using a non-traditional approach of Monte Carlo tolerance analysis to determine the final leadframe and singulation blade design solution. It was found out that the zero lead pullback could be achieved by reducing the leadframe lead to lead distance from 0.275 mm to 0.225 mm and increasing the blade thickness from 0.325 mm to 0.350 mm. Actual results from 10 line stressing lots all showed zero pullback validating the effectiveness of the final design and the use of Monte Carlo tolerance analysis technique. Costly investment for a lead pullback inspection system was avoided and the 100% manual inspection eliminated.

Keywords: Pullback; singulation process; leadframe; singulation blade; Monte Carlo analysis; tolerance analysis; solder wettable; solderable lead sidewall.

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1. INTRODUCTION

One of the requirements of automotive QFN packages is a solder wettable lead sidewall. This would enable automatic solder inspection after the surface mount technology (SMT) process in which the package is mounted on a printed circuit board (PCB). To realize this, there should be no lead pullback as shown in Figs. 1-2.

However, in an automotive QFN package in this study, a lead pullback issue was encountered. As shown in Fig. 3, some mold material was left on the lead sidewall preventing it to become solder wettable. This usually happens when the blade is offset and several tolerance variations come into play. The traditional method of solving a problem involving dimensions and tolerance variations is by using the worst-case tolerance analysis, which is known to be very conservative resulting in tighter dimensional tolerance and high machine accuracy requirements.

In order to delight the customer and protect the company, a 100% manual inspection had been put in place as indicated in Fig. 4. This is already a costly option and it is not ideal. Then it was proposed to invest in an automatic pullback inspection equipment. This solution, however, is also too costly and run counter-intuitive to errorproofing.



Fig. 1. Requirement to have no QFN lead pullback



Fig. 2. Schematic of QFN with and without solder wettable sidewall



Fig. 3. Lead pullback problem



Fig. 4. Manual inspection implemented and investment on inspection machine

Since 100% manual inspection and investing in a new inspection system are not cost-effective solutions to the pullback problem, a better approach was explored in this study. Instead of using the traditional worst case tolerance analysis technique, Monte Carlo tolerance analysis was used to find the best solution.

1.1 Review of Related Work

1.1.1 Tolerance analysis method

Tolerance analysis is very important to shorten package development cycle as it avoids the costly trial and error approach. It can be used to predict the impact of every component tolerance on the final assembly characteristics and improve quality in a cost-effective way.

There are different tolerance analysis methods. As discussed in a comprehensive review by Cao et al. [1], these methods are mainly worst case or statistical case. Worst case, which is a deterministic approach, assumes that each component dimension is at its maximum or minimum limit and the statistical methods are based on the hypothesis that the tolerances follow a certain distribution. Statistical tolerance methods are mainly referred as the root sum squares (RSS) method and Monte Carlo method, of which variations are probability distribution assumed. The conventional RSS or statistical tolerance stacking method tends to be on the optimistic side compared to worst case.

In worst case [2], the assembly tolerance is the sum of the component or detail tolerances. Thus, if the resulting assembly tolerance is too large, one can counteract that by reducing all or some of the detail tolerances, which usually results in a costly part production. However, it is unlikely that all deviations from nominal should arrange themselves in worst case fashion to yield the most extreme assembly tolerance. To address some concerns with worst case, RSS is used. It assumes a normal distribution. centered on that same interval and with a $\pm 3\sigma$ spread equal to the span of that interval, so that 99.73% of all the values fall within this interval. The assembly tolerance in RSS is the square root of the sum of the squares of the detail tolerances. RSS is one of the statistical tolerance analysis methods. Unlike the worst-case method based on the full interchangeability of parts in an assembly, the statistical method is based on the assumption that a reasonable percentage of non-conforming parts may occur [3].

1.1.2 Monte Carlo tolerance analysis

Monte Carlo simulation [4] is a powerful tool for tolerance analysis of mechanical assemblies. It is based on the use of a random number generator to simulate the effects of manufacturing variations on assemblies as illustrated in Fig. 5.

Monte Carlo simulation [5] takes into consideration the probabilistic behavior of the manufacturing process.

Its general procedure is:

- Use a generator to randomly generate n sets of manufactured dimensions in an assembly with specified component distributions.
- (2) Get a sample of assembly functions employing the n sets of manufactured dimensions.
- (3) Estimate the assembly performance parameters, such as mean, standard deviation and reject rate of the assembly.



Fig. 5. Assembly tolerance analysis by Monte Carlo simulation

The number of iterations (n) is very important as pointed out by Barbero et al. [6]. A total of 1000 iterations is sufficient to determine the means and the variations of the output variable, but it is not sufficient to determine the rejection percentage, where at least 10000 iterations should be made.

Monte Carlo method is used in many other applications. It is used to determine the fabrication yields of complex fiber designs for lasers considering the fabrication tolerances [7], simulate assembly error in concentrator photovoltaic (CPV) array [8], and analysis of the effects that random manufacturing errors produce on the radiation diagram of resonant slotted waveguide linear antennas [9]. Monte Carlo simulations have been widely used in the reliability assessment of power electronics systems [10]. The method also finds its use in optical interconnect system under various fabrication and assembly errors [11] and even in addressing main challenges for the metrology of critical dimensions in nanostructures [12]. As we can observed, there are several industry applications of Monte Carlo such as analyzing the effects of geometric deviations on the performance of magnetic gears [13].

2. METHODOLOGY

In this study, Monte Carlo analysis was used in order to do realistic simulation of the interaction of the dimensional components and find a costeffective solution. Actual data for each individual component were collected and used to model the behavior of each component.

2.1 Determination of the Dimensional Components

This study considers the contributors to the lead pullback problem. It was determined that singulation machine and leadframe with the different variations were involved in lead pullback as shown in Fig. 6.

For the singulation machine, we have blade cut width and the cut width offset. While for the leadframe, we have lead-to-lead distance, saw lane offset as well as strip warpage. Actual data of these components (mean, standard deviation) were collected to come up with a better solution.

2.2 Lead Pullback Monte Carlo Analysis

Fig. 7 shows an illustration on how the Monte Carlo analysis was conducted. Monte Carlo simulates actual data for every component that contributes to the pullback issue considering leadframe lead to lead distance, offset, warpage, blade's cut width and different tolerances. When these components are combined in Monte Carlo using an assembly function or transfer equation, the output is the pullback ppm level and even the Ppk with a given statistical distribution. The technique is very powerful and usually gives a more realistic result than worst-case analysis, which only varies component values to their extremes in a manner that produces the worst possible result.

The assembly function of the lead pullback was derived as shown in Fig. 8. This one shows the derivation of the assembly function or transfer function. This is the equation used in the Monte



Fig. 6. Analyzing the contributors to the lead pullback problem



leadframe (lead to lead distance, tolerances, offset, warpage) blade (cut width, tolerances, offset)





Fig. 8. Derivation of assembly function

Carlo calculations being implemented in Minitab statistical software. This considers the factors affecting the lead pullback. To have no lead pullback means that dimension G must be >/= zero. That is, the distance between the

leadframe's lead edge with the cut width edge is positive.

The 1.5 sigma shift [14] was also applied. However stable any process is, over an extended period of time, the environmental conditions change, which causes variation. The environmental changes and the magnitude of this change is 1.5 Sigma (calculated empirically by Motorola as the Long-Term Dynamic Mean Variation).

2.3 Leadframe Redesign

The leadframe design is shown in Fig. 9 and the different blade width and lead to lead distance values are indicated in Fig. 10. There were 2 blades considered: one with 0.325 mm thickness and the other was 0.350mm (thicker). The leadframe design also had 2 options for the lead to lead distance: 0.275mm and 0.225mm (shorter lead-to-lead distance). With these options, Monte Carlo analysis was used to select the best option: one with the best Ppk and passing ppm.

2.4 Validation Runs

There were 10 line stressing lots processed to validate the Monte Carlo analysis used to come up with the final leadframe and blade solution.

Actual pullback inspection (100%) was made. This is in addition to the data collection done on the leadframe and blade design combination where the pullback problem was encountered.

3. RESULTS AND DISCUSSION

Based on the Monte Carlo simulation results in Fig. 11 for option A (0.275mm leadframe lead to lead distance, 0.325mm blade), the zero ppm lead pullback requirement could not be met. The pullback ppm level is quite high at ~9,000. This clearly indicates an issue.

The results for the same leadframe design but using thicker blade (option B) is shown in Fig. 12. This would also not meet the zero ppm pullback requirement for the automotive QFN package in the study. Actual data confirms these results as these were the conditions where the pullback issue was encountered. This failure validation with actual data is providing increased confidence that the Monte Carlo analysis method is matching well with actual observation.



Fig. 10. Options analyzed



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Fig. 11. Monte Carlo analysis results for option A (0.275 LF/ 0.325 blade)



Fig. 12. Monte Carlo analysis results for option B (0.275 LF/ 0.350 blade)

Using a new leadframe with shorter lead to lead distance but still thinner blade (option C), the results show that the zero ppm pullback requirement is met with a Ppk of 1.90 as shown in Fig. 13.

Fig. 14 shows the results with option D (new leadframe design with shorter lead to lead distance and thicker blade). The Ppk is much better at \sim 2.49 compared to using thinner blade.

With process deterioration or 1.5 sigma shift factored in, option C would not meet the zero pullback ppm requirement as shown in Fig. 15. However, the result for option D in Fig. 16 shows that even with 1.5 sigma shift, it would still meet the pullback requirement. The decision was then to pursue this option D with the new leadframe design (0.225 mm lead to lead distance) in combination with a thicker blade (0.350 mm).



Fig. 13. Monte Carlo analysis results for option C (0.225 LF/ 0.325 blade)



Fig. 14. Monte Carlo analysis results for option D (0.225 LF/ 0.350 blade)

The results for the 10 line stressing lots are shown in Table 1. There was no pull back reject encountered in all the lots validating the selected option D.

Table 1. Results of the 10 line stressing lots implementing option D

Lot #	Pullback reject
1	0
2	0
3	0
4	0
5	0
6	0
7	0
8	0
9	0
10	0

Fig. 17 shows the actual package showing zero pullback after implementing the design change identified through Monte Carlo for both leadframe and singulation blade. No mold material could be seen on the lead sidewall.

Table 2 shows the summary of the Monte Carlo tolerance analysis results and comparison with actual pullback reject data. When the thicker blade was implemented without changing the leadframe design, pullback rejection was at 0.0028% or 28ppm. Comparing this to Monte Carlo analysis corresponding to option B, the result is quite close: model = 24ppm; actual = 28ppm. This means that the Monte Carlo model used was accurate. The accuracy of the Monte Carlo analysis prediction was further validated with the line stressing lots for option D.



Fig. 15. Monte Carlo analysis results for option C with 1.5 sigma shift

Option	Monte Carlo Prediction (ppm)	Actual Data (ppm – pullback reject)
A 0.275 LF lead to lead distance/ 0.325 blade	9,041	Rejects much higher, not quantified
B 0.275 LF lead to lead distance / 0.350 blade	24	28
C 0.225 LF lead to lead distance / 0.325 blade	0	not pursued
D 0.225 LF lead to lead distance / 0.350 blade	0	0





Fig. 16. Monte Carlo analysis results for option D with 1.5 sigma shift





4. CONCLUSION

Solving problems that involved tolerance variations could be done using Monte Carlo tolerance analysis to provide basis for improving the design instead of implementing costly solutions. This method is more realistic than the traditional worst-case analysis, which only results in conservative and costly decisions.

Automotive QFN singulation pullback issue could be eliminated using a thicker singulation blade (0.350 mm) and new leadframe design (0.225 mm lead-to-lead distance). Results for this selected solution showed zero ppm pullback. Actual results with 10 line stressing lots validated the effectiveness of Monte Carlo analysis in determining design solution resulting in the elimination of 100% manual inspection and a cost avoidance for the automatic inspection machine investment.

DISCLAIMER

The products used for this research are commonly and predominantly use products in our area of research and country. There is absolutely no conflict of interest between the authors and producers of the products because we do not intend to use these products as an avenue for any litigation but for the advancement of knowledge. Also, the research was not funded by the producing company rather it was funded by personal efforts of the authors.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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