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# Development of Solder Joint Void Metrology to Monitor Solder Joint Quality in Printed Circuit Board Assemblies

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**Abstract**
Solder joint reliability is determined by multiple factors, one of which is voiding. The formation of voids in solder joints is caused by entrapped air during the reflow process and could be challenging to eliminate entirely. When voiding exceeds a certain level, it may lead to joint failure and is therefore important to quantify. X-ray inspection is a nondestructive method that can be used to measure voiding, but currently available X-ray equipment has limitations. Automated X-ray Inspection tools (AXI) are fast but lack accuracy, whereas 2D X-ray tools are accurate but slow and cannot be used in a production environment. We will be showing a new method that we developed using Deep Learning (DL) to improve the speed of void measurement with a 2D X-ray tool while still maintaining accuracy. Our DL method is a two-phase approach. The initial phase involves the detection of solder ball area and then segmentation to detect the boundaries of the solder ball. The second phase involves segmentation to detect voids. We have achieved 99.9% solder ball detection and area segmentation, and 99.5% void segmentation. The capability of the Deep Learning method used is then determined using Measurement Capability analysis.

Key words: solder joints, metrology, voiding.

**Introduction**
Voiding is a defect mode that could lead to reliability issues in the long run, and to be addressed properly, voiding needs to be quantified reliably without adding bottlenecks to the design process. Solder paste is comprised of metal spheres and flux which binds the paste component and enables solder joint formation during the reflow process. Flux outgassing during the reflow process can result in trapped gases that could lead to voiding in solder joints. When voids exceed 30% [1] of the entire solder joint volume, that joint would be considered defective and should be rejected. Solder joint dimensions are also of great importance to combine with voiding data due to the implications they could have on an assembled ball grid array (BGA). Width measurements of solder joints are used in solder joint mathematical modelling (SJMM) to help packaging engineers predict the behavior of Ball Grid Arrays (BGA) after the Surface Mount Technology (SMT) process. Varying build parameters such as solder paste volume could have significant effects on the size of solder balls, which could lead to bridging or open defects during reflow. SJMM can be used to help predict these issues while in the process design phase. SJM models can predict the solder joint dimensions of a BGA before going into manufacturing. Solder joint width measurements are used to validate SJM models by comparing the predicted solder ball dimensions against actual solder ball measurements coming from assembled packages. Here arises the importance of having a capable metrology system that can provide Solder Joint Width and Voiding Measurements (SJWM, SJVM, SJWVM) to help in SJMM and in measuring voids.

There are a few methods in the industry to help collect SJWVM data. These can be time consuming, provide little data, and can be destructive, e.g., cross sections. Automated X-ray Inspection tools are an alternate solution. They are capable of producing large amounts of data in a relatively short time. Such tools are very useful in a production environment, but they usually lack the proper accuracy and high resolution required in a technology Development (TD) environment. A third option would be to use 2D X-ray tools that provide high resolution images, are simple to use, and can be programed to create inspection and data collection routines. Such tools can provide accurate measurements but could be slow and they fail to correlate pin names to solder balls. In other words, they cannot provide actual pin names found in CAD files to the targeted solder ball, but instead they provide arbitrary names to these solder balls. It is very time consuming trying to correlate the arbitrary pin names to their true CAD names to be helpful in the SJM modelling process. 2D X-ray tools often have a degree of automation embedded in the software, but they do require an operator to touch up or improve on the collected data. An automated data collection process has a tendency to miss solder balls with a different grey scale contrast or when there are smaller features in the field of view.

In a process development environment, the quantity and quality of the data is very crucial to produce proper SJM models, hence it becomes important to have a process that is capable of producing a sufficient and accurate amount of data. It needs to be fast, and without adding more burden to the process. In this paper we are showing what could be done when using a 2D X-ray system to collect high resolution images and process them with Deep Learning (DL) using

Artificial intelligence (AI) in order to produce accurate solder joint width and void measurements.

**Deep Learning Training and Inferencing**

Artificial Intelligence is becoming more attractive to use in the printed circuit board assembly (PCBA) industry due to the ability to learn patterns and save time and effort compared to traditional methods. AI in our case was the method to use due to ease of data training that was available to us. Intel Corp. developed AI software that helps with data training that significantly reduces the training efforts. The AI environment allows us to upload a set of images and assign characteristics and labels to these images. The first few images will require manual labeling by the user until it learns the targeted patterns. The AI environment will then predict and label the targeted features for the rest of the images while providing a confidence for each selection. The user would need to approve these selections or, in some cases, correct them. The output model based on TensorFlow was converted into OpenVINO model which is light weight for any x86 CPU to run efficiently.

There are three steps used in training of the used datasets. The first step is to detect the location of the desired feature, in our case it's solder joints. The AI environment highlights the solder location in order to send to the next step which is edge detection segmentation. The DL method segments the solder joint and detects the edge in order to highlight the solder. The third step is void segmentation where voids are detected and highlighted within the solder joint. Figure 1 shows the solder joint detection and segmentation process.

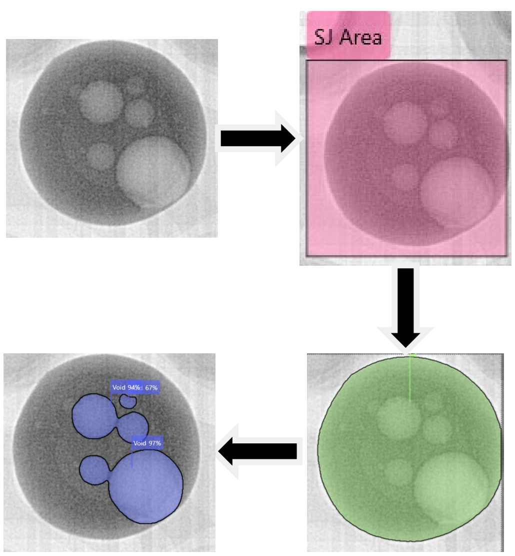


**Figure 1.** Solder joint detection and segmentation process in the AI environment.

The AI environment provides a confidence for each feature detection. We have achieved 99.9% in detection accuracy for solder joint locations as well as solder joint edge detection. We also achieved 93% in void detection accuracy; the lower accuracy resulted from smaller sized voids relative to the solder joint as well as the 2D X-ray image quality. Void segmentation on the other hand was 99.5%. 2D X-ray image shows all layers of a solder joint in a single 2D image, which prevents some details from being visible and reduces the quality of the visible features.

**Graphical User Interface**

This previous activity would only detect the solder joint and voiding. We still need further processing to obtain the solder joint measurements and void analysis. This is done using a graphical user interface with imbedded code that would complete the analysis. In addition, training data using the AI environment is user friendly but it's not production friendly. It requires time, can only be done offline, and won't provide any measurements, therefore we had to develop a graphical user interface (GUI) to complete the task. The GUI was created to be production line friendly by setting up recipes for products and then running them in production mode. This allows for a shorter overhead time, faster production time, and a better control of the results' quality. The GUI home page is shown in Figure 2.

The first step requires linking the DL training data with the GUI. This will only be done once during the first GUI use, or when the training dataset is updated. The GUI consists of two operations, one operation to create recipes and another to run these recipes in production mode.

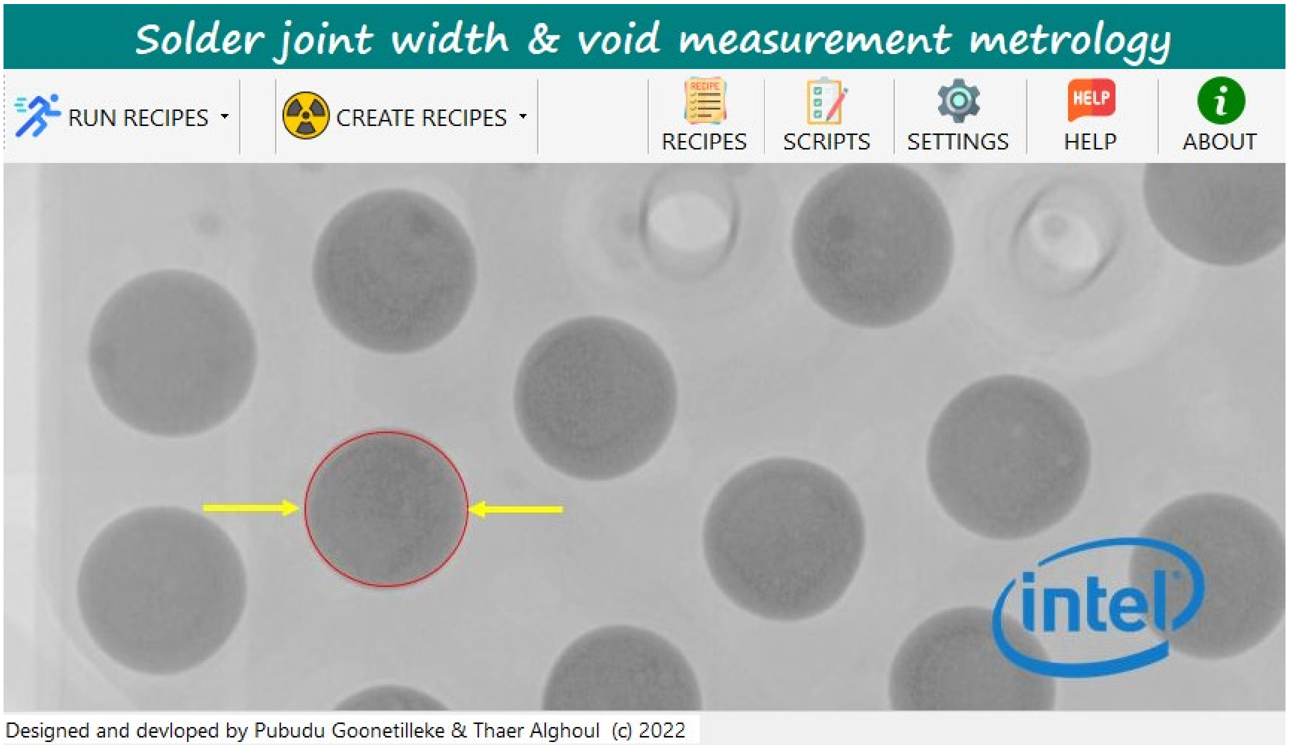


**Figure 2.** SJWVM GUI home page.

The GUI will use the solder joints and voids detected using the DL to count pixels. The pixels counted represent the average solder joint area, the average solder joint width, the maximum solder joint width, and the total void area within the solder joint. These measurements need to be converted to a useful measurement unit. We use an ASTM stainless steel standard with three holes of different know sizes to calculate a conversion factor, shown in Figure 3. The diameter of the standard is measured in pixels and a conversion factor is calculated based on the known diameter of the standard. This way we can convert any pixel measurement to microns by dividing the pixel measurement by pixels/microns, as shown in Figure 4.

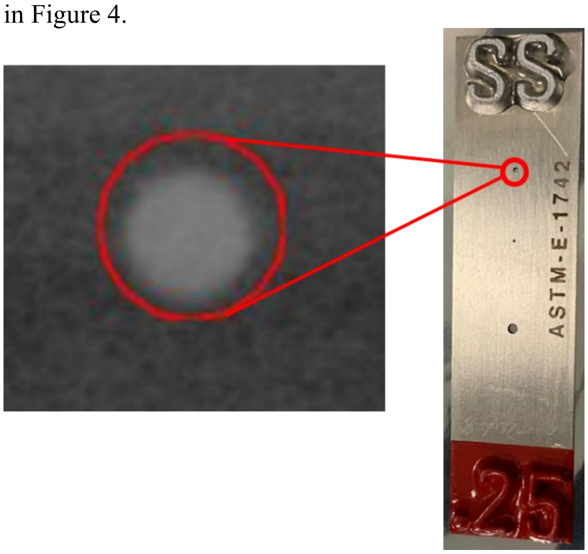


**Figure 3.** ASTM standard with three known hole diameters used in calculating conversion factor.

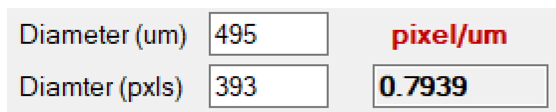


**Figure 4.** Pixel to micrometer conversion operation in the SJWVM GUI.

Two file types are needed for recipe creation, a CAD file, and an image. The CAD file should have the targeted solder joints that need to be measured while the image is a 2D X-ray image of the same solder joints. Once these files are imported to the GUI, the first step would be to align the CAD data to the x-ray image as shown in Figure 5. Once the pin alignment is completed, the AI recipe type can then be chosen from two options, solder joint width measurements only, or width and voiding measurements. The recipe can then be saved and tested.

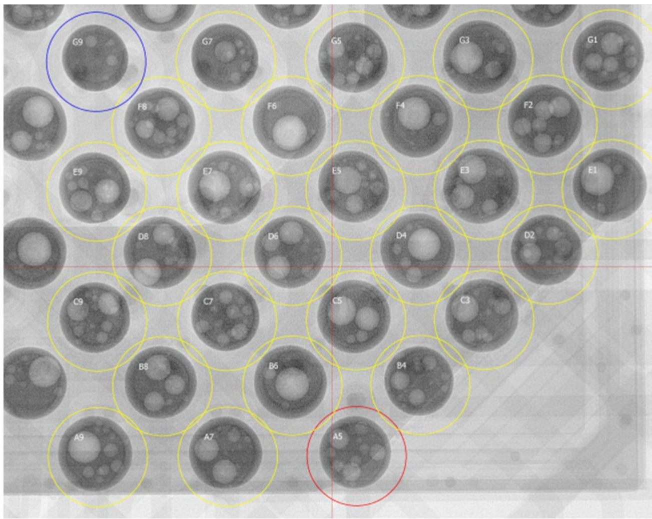

**Figure 5.** Solder ball and pin name alignment.

Edge detection using AI is implemented over a few steps. In the first step, the AI algorithm identifies the general location of a solder joint then it isolates from the original image to be processed. The algorithm starts detecting the edge of the ball, and then the voids. The last step combines both the ball and voids detected and adds them to the original image. The solder ball area, width, and void total area are measured and recorded in pixels. The pixel measurements are then converted to microns using the conversion factor obtained earlier. Total void area % is also calculated. All results are saved in a separate file that contain the solder ball information along with the measurements. A sample of the output results are shown in figure 5. Recipe creation allows for providing measurements in production mode where multiple board data can be uploaded and inspected together. Figure 6 shows a screenshot of the production page.

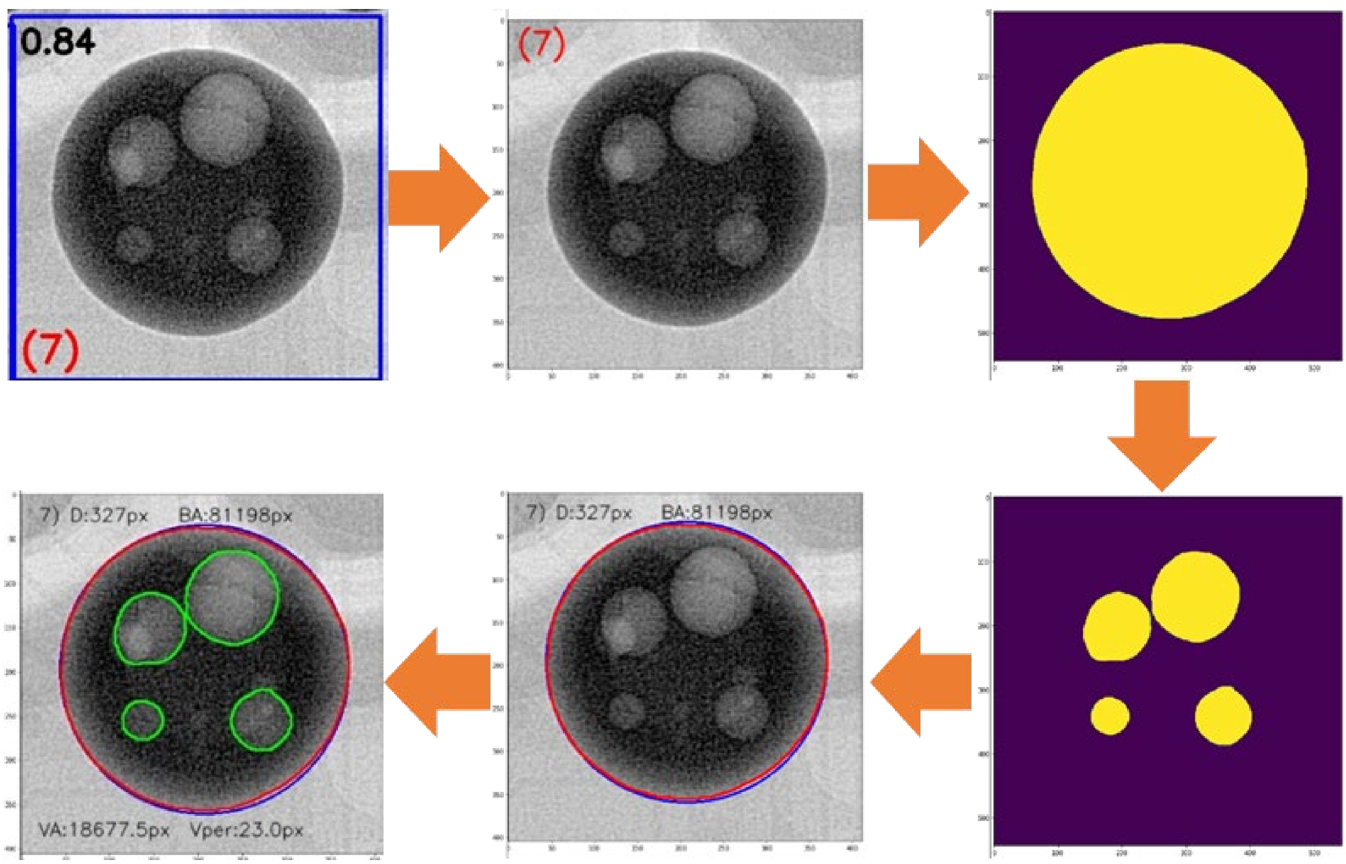


**Figure 5.** solder joint edge and void detection process using AI steps.

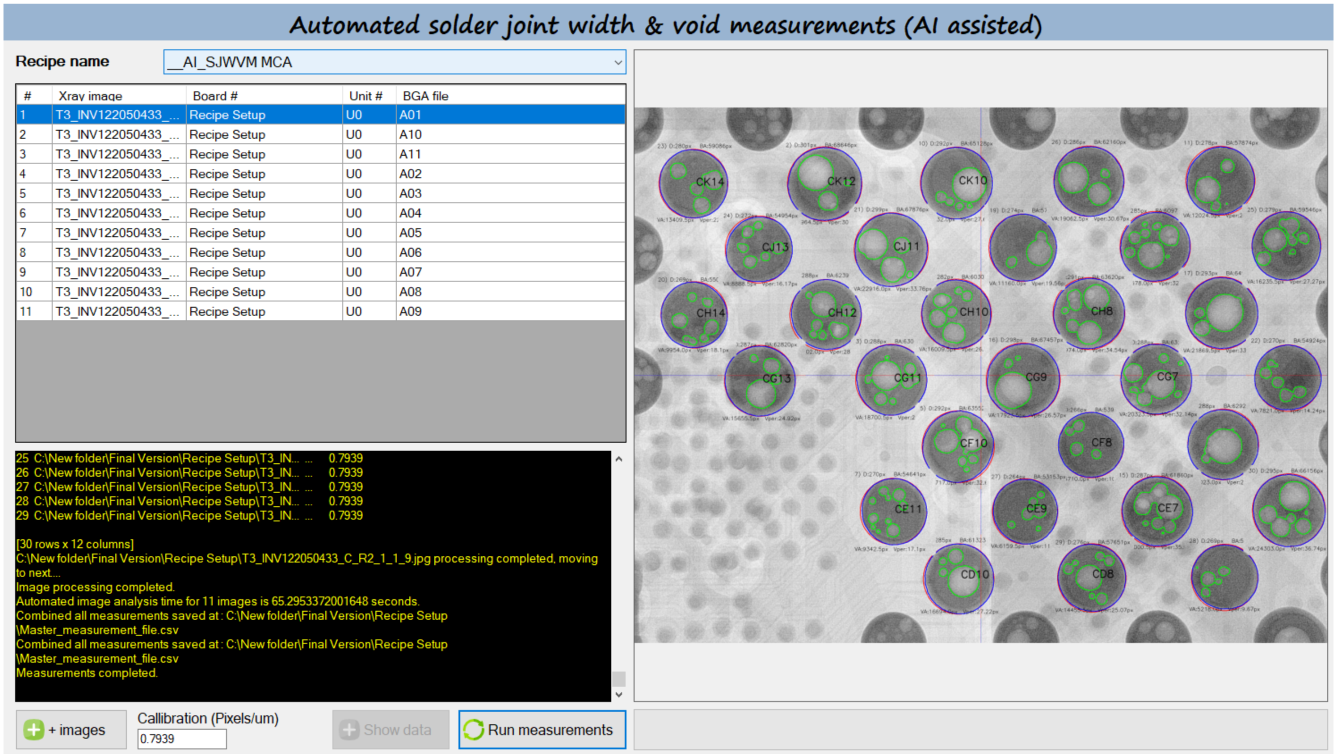


**Figure 6.** SJWVM production mode home screen.

## Experiment

Metrology systems created need to be assessed before being released to a production environment to determine the reliability of measurements produced, therefore a Measurement Capability Analysis (MCA) is performed. An MCA is divided into three parts, the first part is to determine the accuracy of the produced measurements. In accuracy measurements, 16 measurements of solder joints are collected, and the mean of these measurements is compared against the true value of each of these solder joints. The allowable technical delta for the measurements is 5µm, which means that each measurement is allowed to be within ±5µm of the actual measurement for width and ±10% for void area measurements. The second part of the MCA is repeatability which is to determine measurements' variation when these measurements are collected under the same circumstances. Thirty measurements for the same solder joints are collected and the variation is determined. The passing criterion for repeatability is to have zero out of control measurements (OOC) and a precision over tolerance (P/T) value to be less than 20%. The third part is reproducibility where the goal is to determine measurements variation under different data collection conditions. Reproducibility data collection should be done under different conditions. Conditions used include three operators collecting data from three different printed circuit board assemblies (PCBA) during three different times of the day. The criteria to pass reproducibility is to have zero OOCs and a P/T ratio under 30%. Table one shows the Measurement Capability Analysis data collection summary.

**Table 1:** Measurement Capability Analysis Experiment Summary.

| Test | Method | Condition | Result |
|---|---|---|---|
| Accuracy | • 10 measurements | • Delta less than 5µ (SJWM)<br>• Delta less than 10% (SJVM) | Pass |
| Repeatability | • 30 dynamic measurements | • No OOCs<br>• P/T less than 20% | Pass |
| Reproducibility | • 3 boards<br>• 3 operators<br>• 3 different times | • No OOCs<br>• P/T less than 30% | Pass |

## Results

To determine the reliability of the solder joint width and void measurements, we needed to determine the accuracy of these results. Eight solder balls were measured 16 times and the mean for these balls was evaluated. For all these solder balls, the mean was found to be within ±5µm from the known value of each of them, shown in Figure 7. Total voiding % was also evaluated for the same solder balls. The accuracy technical delta for total voiding % is ±10%. All solder balls had a mean value that varied by less than 1% from the true total voiding % as shown in Figure 8. This provides a confidence that collected measurements using our new system are reliable and can be trusted when used in solder joint mathematical models.

| Parameter | Standard | Mean | Bias | Std Dev | Technical Delta | Lower 95% Mean | Upper 95% Mean | Technical Evaluation |
|---|---|---|---|---|---|---|---|---|
| G9 | 309.3 | 305.38 | -3.9198 | 0.08825 | 5 | 305.317 | 305.443 | Bias TE to 0 |
| G3 | 321.95 | 322.712 | 0.76186 | 0.06385 | 5 | 322.666 | 322.758 | Bias TE to 0 |
| F6 | 292.46 | 289.917 | -2.5431 | 0.07441 | 5 | 289.864 | 289.97 | Bias TE to 0 |
| F4 | 315.6 | 314.382 | -1.2179 | 0.07697 | 5 | 314.327 | 314.437 | Bias TE to 0 |
| F2 | 317.62 | 317.497 | -0.1231 | 0.04775 | 5 | 317.463 | 317.531 | Bias TE to 0 |
| E9 | 309.3 | 307.925 | -1.3747 | 0.0568 | 5 | 307.885 | 307.966 | Bias TE to 0 |
| E7 | 309.3 | 306.081 | -3.2191 | 0.05529 | 5 | 306.041 | 306.12 | Bias TE to 0 |
| E3 | 311.43 | 307.101 | -4.3292 | 0.07091 | 5 | 307.05 | 307.152 | Bias TE to 0 |

**Figure 7.** SJWM accuracy measurements results.

| Parameter | Standard | Mean | Bias | Std Dev | Technical Delta | Lower 95% Mean | Upper 95% Mean | Technical Evaluation |
|---|---|---|---|---|---|---|---|---|
| G9 | 24.3 | 25.761 | 1.461 | 0.50518 | 5 | 25.3996 | 26.1224 | Bias TE to 0 |
| G3 | 24.7 | 27.52 | 2.82 | 0.14384 | 5 | 27.4171 | 27.6229 | Bias TE to 0 |
| F6 | 14.9 | 18.922 | 4.022 | 0.59095 | 5 | 18.4993 | 19.3447 | Bias TE to 0 |
| F4 | 27.2 | 27.263 | 0.063 | 0.4719 | 5 | 26.9254 | 27.6006 | Bias TE to 0 |
| F2 | 32.8 | 34.986 | 2.186 | 0.53161 | 5 | 34.6057 | 35.3663 | Bias TE to 0 |
| E9 | 24.9 | 29.37 | 4.47 | 0.40028 | 5 | 29.0837 | 29.6563 | Bias TE to 0 |
| E7 | 26.8 | 30.43 | 3.63 | 0.36512 | 5 | 30.1688 | 30.6912 | Bias TE to 0 |
| E3 | 19.3 | 22.476 | 3.176 | 0.52621 | 5 | 22.0996 | 22.8524 | Bias TE to 0 |
| E1 | 24.9 | 29.37 | 4.47 | 0.40028 | 5 | 29.0837 | 29.6563 | Bias TE to 0 |

**Figure 8.** SJVM accuracy measurements results.

Determining the accuracy of the system is crucial to build trust in the new process, but we also need to determine the system's variation, therefore we collected 30 measurements for another set of solder balls and evaluated the repeatability of the system. Repeatability is first determined by calculating the precision over the tolerance value (P/T), which is equal to six times the value of the measurements' standard deviation divided by the range of the spec limits. P/T ratio should be less than 20% to pass this repeatability. The second portion of the test includes plotting the measurements in an X-bar ($\overline{X}$) chart to determine if there are any out-of-control data points. 13 solder balls were selected for the repeatability evaluation. Each of these solder balls were X-rayed 30 times to get their measurements. Solder joint width measurement repeatability analysis was carried out and it was found that all had a P/T ratio of less than 20% and none had any out-of-control data points. The voiding analysis also showed similar results. This leads to the repeatability analysis passing for both the width and voiding capabilities of our new software. Table 2 shows SJWM repeatability analysis and Table 3 shows SJVM repeatability analysis.

**Table 2:** SJWM Repeatability Analysis Results.

| Pin Name | SJWM Repeatability | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | LSL | LCL | Diameter Average | UCL | USL | Diameter ST. Dev | P/T | OOC Count |
| E9 | 290.6 | 294.8 | 295.6 | 296.4 | 300.6 | 0.3 | 15.6 | 0 |
| CK48 | 300.6 | 305.1 | 305.6 | 306.2 | 310.6 | 0.2 | 11.6 | 0 |
| CP50 | 299.8 | 304.2 | 304.8 | 305.4 | 309.8 | 0.2 | 11.7 | 0 |
| D22 | 289.3 | 293.7 | 294.3 | 294.9 | 299.3 | 0.2 | 12.0 | 0 |
| E23 | 278.2 | 282.4 | 283.2 | 283.9 | 288.2 | 0.3 | 15.2 | 0 |
| E55 | 288.4 | 292.8 | 293.4 | 294.0 | 298.4 | 0.2 | 12.3 | 0 |
| E9 | 290.6 | 294.8 | 295.6 | 296.4 | 300.6 | 0.3 | 15.6 | 0 |
| F22 | 290.9 | 295.3 | 295.9 | 296.4 | 300.9 | 0.2 | 11.1 | 0 |
| F28 | 294.4 | 298.7 | 299.4 | 300.0 | 304.4 | 0.2 | 12.7 | 0 |
| F50 | 293.2 | 297.5 | 298.2 | 298.8 | 303.2 | 0.2 | 13.3 | 0 |
| G21 | 287.9 | 292.3 | 292.9 | 293.4 | 297.9 | 0.2 | 11.7 | 0 |
| H42 | 287.0 | 291.4 | 292.0 | 292.5 | 297.0 | 0.2 | 10.7 | 0 |
| C3 | 292.7 | 296.9 | 297.7 | 298.4 | 302.7 | 0.3 | 15.3 | 0 |

**Table 3:** SJWM Repeatability Analysis Results.

| Pin Name | SJVM Repeatability | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | LSL | LCL | Void% Average | UCL | USL | Void% St. Dev | P/T | OOC Count |
| E9 | 29.4 | 28.5 | 29.4 | 30.4 | 39.4 | 0.3 | 18.6 | 0 |
| CK48 | 29.7 | 29.0 | 29.7 | 30.3 | 39.7 | 0.2 | 13.3 | 0 |
| CP50 | 29.1 | 28.3 | 29.1 | 30.0 | 39.1 | 0.3 | 16.8 | 0 |
| D22 | 28.9 | 28.4 | 28.9 | 29.5 | 38.9 | 0.2 | 11.1 | 0 |
| E23 | 32.2 | 31.3 | 32.2 | 33.1 | 42.2 | 0.3 | 17.9 | 0 |
| E55 | 26.8 | 26.3 | 26.8 | 27.4 | 36.8 | 0.2 | 11.8 | 0 |
| E9 | 29.4 | 28.5 | 29.4 | 30.4 | 39.4 | 0.3 | 18.6 | 0 |
| F22 | 34.7 | 34.0 | 34.7 | 35.5 | 44.7 | 0.2 | 14.4 | 0 |
| F28 | 31.3 | 31.0 | 31.3 | 31.7 | 41.3 | 0.1 | 6.8 | 0 |
| F50 | 30.2 | 29.5 | 30.2 | 30.9 | 40.2 | 0.2 | 14.4 | 0 |
| G21 | 26.6 | 25.7 | 26.6 | 27.6 | 36.6 | 0.3 | 19.1 | 0 |
| H42 | 30.4 | 29.6 | 30.4 | 31.3 | 40.4 | 0.3 | 16.4 | 0 |
| C3 | 32.0 | 31.1 | 32.0 | 32.9 | 42.0 | 0.3 | 17.8 | 0 |

The final part of the MCA is to evaluate the reproducibility of the data to check the variation resulting from different factors like different operators collecting the measurements and the time effect. This is a critical part of our evaluation; we want our new system to produce similar results no matter what time of the day it is or who is collecting the data. We have chosen 10 solder balls from 3 boards to be evaluated in this test.

In figure 9 below, we show the solder ball variation. We saw that all measurements varied within ±1µm from their mean value except for limited cases where they varied by ±2µm. This shows the stability of the new system. Obtaining the overall results of the reproducibility analysis showed a P/T ratio of just 1.5%, well below the 30% mark, shown in Figure 10. Similarly, the voiding analysis also showed limited variation. Most of the voiding measurements varied within ±2% of the mean total voiding %, shown in Figure 11. The overall P/T ratio for the system was 19.6% which also meets the reproducibility requirement, shown in Figure 12.

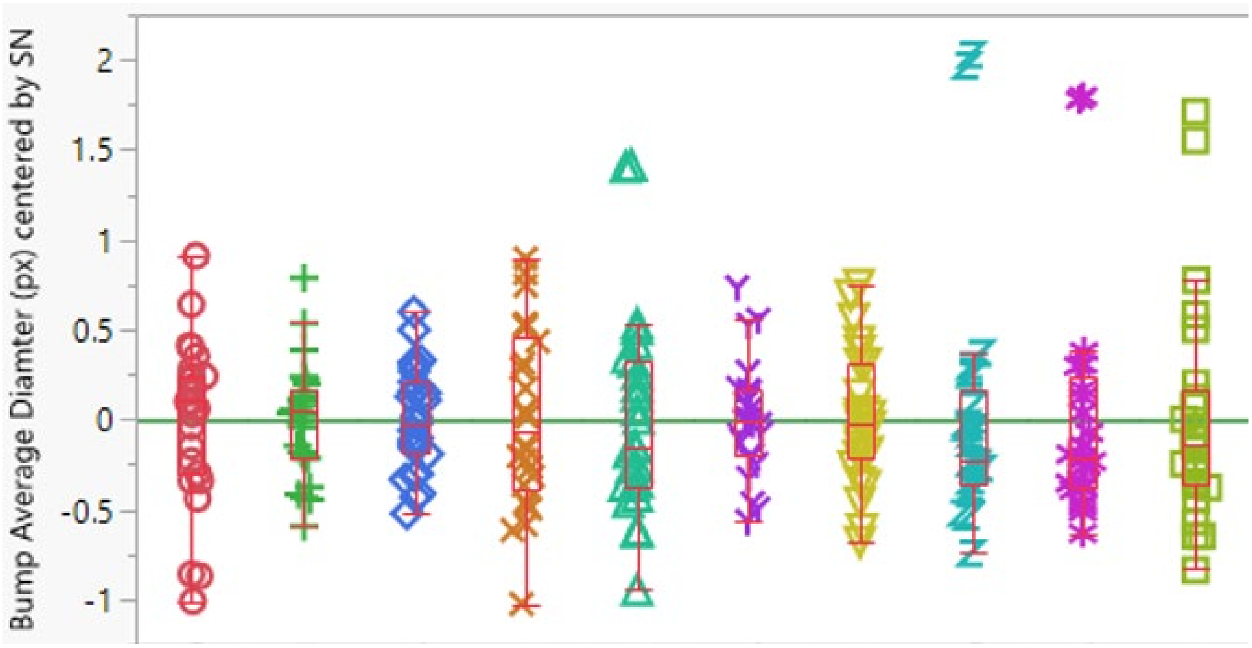


**Figure 9.** SJWM reproducibility: individual measurement variation.

**Overall Reproducibility Evaluation Summary Table**

| Parameter | LSL | Process Mean | USL | Process Sigma | Pseudo Sigma(ms) | Pseudo P/T Ratio (%) | Sigma(ms) | P/T Ratio (%) | Statistical Evaluation |
|---|---|---|---|---|---|---|---|---|---|
| Bump Average Diamter (px) | 250 | . | 350 | . | 0.4831 | 2.9 | 0.24911 | 1.5 | Capable |

**Figure 10.** SJWM reproducibility results.

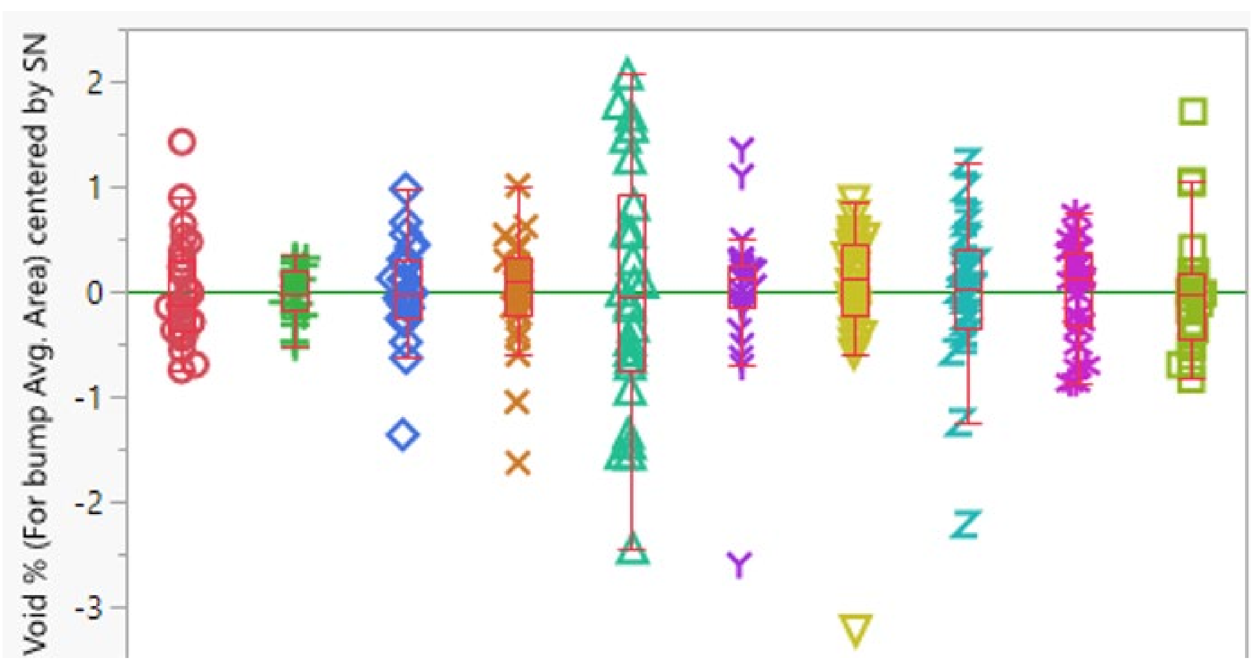


**Figure 11.** SJVM reproducibility: individual measurement variation.

| Overall Reproducibility Evaluation Summary Table | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Parameter | LSL | Process Mean | USL | Process Sigma | Pseudo Sigma(ms) | Pseudo P/T Ratio (%) | Sigma(ms) | P/T Ratio (%) | Statistical Evaluation |
| Void % (For bump Avg. Area) | 15 | . | 35 | . | 0.65485 | 19.6 | 0.62749 | 18.8 | Capable |

**Figure 12.** SJVM reproducibility results.

The previous results showed that our new solder joint width and void measurement system met the measurement capability analysis requirement by passing accuracy, repeatability, and reproducibility parts of the evaluation. These results give us confidence in the measurement system we are using and provides solid data that can be used in solder joint mathematical models.

In this study we used Intel's client packages in the AI training process. We did see there were some discrepancies when using larger BGAs with an Integrated Heat Shield (IHS) attached to them, which introduced light and dark regions that the AI detection couldn't account for. In future efforts, we will be using more of these larger BGAs for training purposes to mitigate the effect of the IHS. We tested a commercially available 2D X-ray tool's capability in measuring such samples and they failed in providing accurate measurements for such packages. In addition, such tools require a few minutes to collect package measurements, and a few more hours to correlate measured data to their respective solder ball names since CAD import features in such tools do not perform well for the intended task.

## Time Improvement

Data collection and analysis consume a lot of time when there is a manual process. The old process that was used to collect solder joint width and voiding measurement took about 1 hour to create a recipe on a 2D X-ray tool for 10 BGAs. Once the measurements are collected, another 4 to 5 hours are needed to correlate the arbitrary pin names given by the tool to the actual pin names that are provided in the original CAD file. This is an extra burden that prolongs the process. We saw a significant improvement in the data collection process as well as significant time reduction when AI was used for void and width measurements. The AI algorithm reduced the data collection process to about 0.5 hours since the AI algorithm did all the work to detect solder balls and provide void and width measurements without a need for an interference from an operator for post processing or pin name correlation. Time reduction is in addition to the increase of solder ball void width data quantity collected. There is a 200% increase in collected solder joints measured compared to the old process.

## Conclusion

Solder joint voiding and width measurements collection is an important metrology to assess the reliability of solder joints and to predict possible defects in BGAs. Solder joint mathematical modelling is a driver to improve data collection methods used to compare real life data with predicted data. In order to collect real life data, we had to collect a sufficient number of accurate measurements in a timely manner. Collecting measurements from 2D X-ray images of solder balls and processing them using AI helped in reducing the time to create SJWVM recipes as well as reducing operators' effort to collect and process solder ball data. A measurement capability analysis was performed to certify the new process and determine its capability to produce reliable measurements that can be used in SJMM. The MCA showed the data collected had an accuracy with ±5µm for width measurements and ±10% for voiding measurements. Results using our new process showed a reduction in data collection time and an increase in collected data.

## References

[1] IPC Acceptability of Electronic Assemblies (IPC-A-610), Rev H, page 8.