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LEVERAGING MACHINE SIGNALS FOR DEVICE-LEVEL QUALITY DETECTION AND AUTOMATIC ROOT CAUSE ANALYSIS IN SEMICONDUCTOR WIRE BONDING

Kenneth J. Braakman[1], D. Martin Knotter[2], Alp Akcay[3], and Ivo Adan[3]

[1]Total Quality Operations, NXP Semiconductors N.V., Eindhoven, THE NETHERLANDS
[2]Product Diagnostic & Quality Center, NXP Semiconductors N.V., Nijmegen, THE NETHERLANDS
[3]Department of Industrial Engineering & Innovation Sciences, Eindhoven University of Technology, Eindhoven, THE NETHERLANDS

ABSTRACT

This paper focuses on leveraging machine signal data from wire bond machines by building a data-driven solution to enhance root cause analysis efficiency and real-time quality control in semiconductor wire bonding. Traditional root cause analysis is time-consuming, labor intensive and performed in hindsight. We performed experiments at NXP Semiconductors N.V. that mimicked wire bonding problems caused by forming gas, and subsequently used the resulting real-world data to overcome the traditional root cause analysis challenges. We show that random forest classification models can successfully differentiate between standard and problematic wire bond manufacturing conditions, identifying significant machine-signal-related features associated with forming gas issues. The study demonstrates the effectiveness of linking machine-signal-related features to root causes, enabling proactive detection of potential failures during wire bonding.

1 INTRODUCTION

The semiconductor industry faces challenges arising from reducing product life cycles (Chen-Fu Chien and Lin 2020), the ever-expanding market demand and the ongoing trend of integrated circuits (ICs) decreasing in size and increasing in complexity (Espadinha-Cruz et al. 2021). When dealing with more complex products the risk of failures is higher (Lim et al. 2017) and more time is needed to find the root causes of these failures. Moreover, more failures lead to a higher amount of wasted resources. Considering the importance of sustainability in combination with the aforementioned challenges it is essential that the huge amount of data that is generated in semiconductor companies nowadays will be leveraged to a greater extent to increase root cause analysis efficiency and to enable the prediction and prevention of product failures, which is also a fundamental part of the Zero-Defect Manufacturing (ZDM) concept as described by Psarommatis et al. (2022).

The work performed in this paper is based on real-world data from a use case at NXP Semiconductors N.V.'s back-end fab in Kuala Lumpur, Malaysia. The back-end manufacturing process consists of several steps of which the main steps are depicted in Figure 1. The back-end fab receives finished wafers from the front-end fabs and starts the process with wafer backgrinding where the wafers are made thinner by removing material from the backside. After that, the wafers are diced into individual dies and each die is then attached to a leadframe or ball grid array substrate. During wire bonding the dies or ICs are interconnected with fine conductive wires to the leadframe or substrate. A protective cover is given to the IC in the molding step after which, the product is ready for final testing and packing.

In this paper, we focus on wire bonding which is considered to be one of the most critical process steps of the back-end manufacturing process. To be more specific, we consider thermosonic ball bonding. The process steps per wire are depicted in Figure 2. The process starts with forming a Free Air Ball (FAB) using an electronic spark, after which the bond ball is created by bonding the ball to the bond pad on the

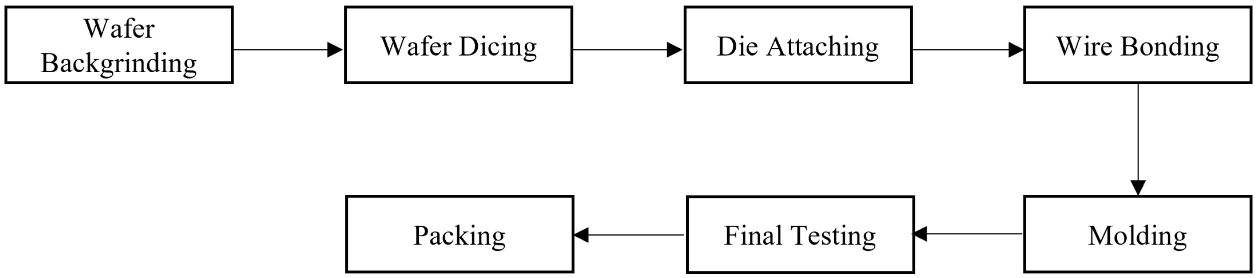


Figure 1: Main steps in the back-end manufacturing process.

IC. During this process a so-called InterMetallic Compound (IMC) is formed which keeps the ball on the bond pad. A higher coverage means higher mechanical strength and vice versa. Subsequently, the capillary creates a stitch bond on the leadframe or substrate in a similar way. Important machine parameters to successfully create the bond ball and the stitch bond are heat, pressure, and ultrasonic vibration (Rooney et al. 2005). On top of that, properties of the bond and stitch pad, such as hardness and cleanliness may affect the wire bond process, but these parameters are in general not systematically measured.

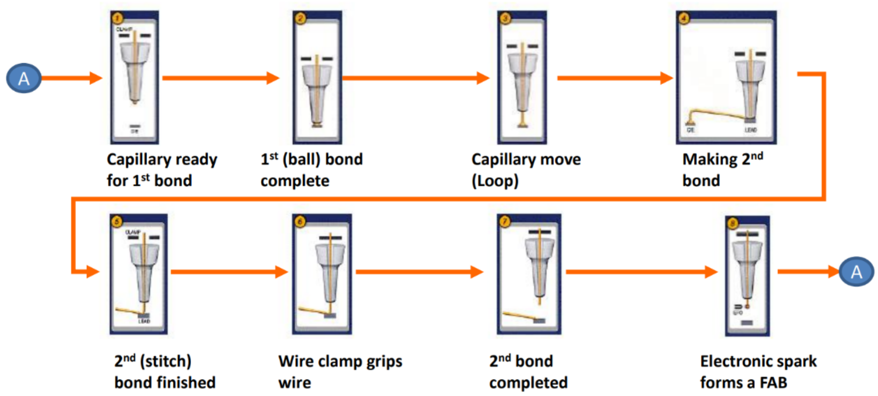


Figure 2: Thermosonic ball bonding process steps (Choorat 2015).

Due to the increasing complexity and smaller size of ICs, more wires have to be bonded on a smaller area. This may lead to more product failures because an IC already fails if even a single wire is not bonded properly. One of the main challenges in wire bonding is that the quality is often only measured on sample base using destructive tests. Examples of these types of tests used in industry are the wire pull test and the ball shear test as discussed by Wang and Sun (2009) and the IMC coverage test as presented by Zachariasse et al. (2013). There are also different non-destructive sensing modalities to test wire bond quality, such as optical, radiological, acoustical, and infrared thermography (Alam and Kehtarnavaz 2022). However, these types of testing techniques also have limitations as not all failure modes can be detected, no real-time quality control is possible, and in practice is not always available for each wire bond process. Moreover, another limitation is that the current spatial resolution does not suffice to meet the requirements of IC miniaturization in the semiconductor industry (Aryan et al. 2018). The use of these types of quality tests thus lead to a lack of effective control or detection on wire bond quality. Another challenge is that there are many failure modes related to wire bonding and each failure mode can have many root causes (Dah-Chuan Gong and Hou 2017). Finding these failure modes and performing corresponding root cause analysis takes a lot of manual effort.

In this work, we focus on the machine signal data generated by wire bond machines and build a data-driven solution to tackle the aforementioned challenges. If machine-signal-related features could be linked to potential IC failures and corresponding root causes, this would lead to more real-time wire bond quality control. The objective of this paper is to build a data-driven solution to find wire bond machine-signal-related features that are able to detect the IC quality during wire bonding and connect it to a possible root cause in case of potential failure. To the best of our knowledge, we are the first in semiconductor wire bonding manufacturing that links features related to machine signals directly to the root cause of a failure, instead of only linking them to the failure itself.

The remainder of this paper is organized as follows. In Section 2, we will give some additional background information on the specific wire bond failure mode and corresponding root cause. Further, we will elaborate on relevant literature in this section. Then in Section 3 we will discuss our modeling approach and subsequently in Section 4 we will present our results. We provide a discussion in Section 5 and managerial implications in Section 6. Finally, we will give our conclusions and recommendations for future work in Section 7.

2 BACKGROUND AND RELATED WORK

2.1 Failure mode

As the objective of this paper is to prove the concept of linking machine-signal-related features to the root cause of a failure, we decide to focus on one specific failure mode out of many failure modes that could result in a so-called non-stick on pad (NSOP) event. NSOP is the effect of the failure in the process of bonding a bond ball to a bond pad of the IC. NSOP occurs when the IMC coverage is too low. If this happens during the wire bonding process, then the wire bond machine automatically stops as it does not measure electrical current running through the wire and IC. However, the real challenge lies in detecting so-called near NSOP events. In these cases, the IMC coverage is just enough to survive the wire bonding process, but will fail downstream the manufacturing process, or even worse, in the field. Unfortunately, the detectability of these near NSOP events is limited. Figure 3 shows a hypothetical IMC process performance distribution (excluding random defects on bond pad). The left (blue) dotted line represents the IMC fail level and in case the IMC coverage falls below this value, an NSOP event occurs during wire bonding and the wire bond machine automatically stops. The right (yellow) dotted line represents the critical IMC level and IMC coverages above that value are sufficiently high to survive the IC product lifetime. The group of near NSOP events is represented by the IMC coverages that fall between the IMC fail level and the critical IMC level. In a healthy manufacturing process, no (near) NSOP events occur, which is represented by the right (black) hypothetical Normal distribution. However, over time a process shift can occur, as represented by the (grey) hypothetical Normal distribution shifted to the left, which leads to IMC coverages falling below the critical IMC level or IMC fail level.

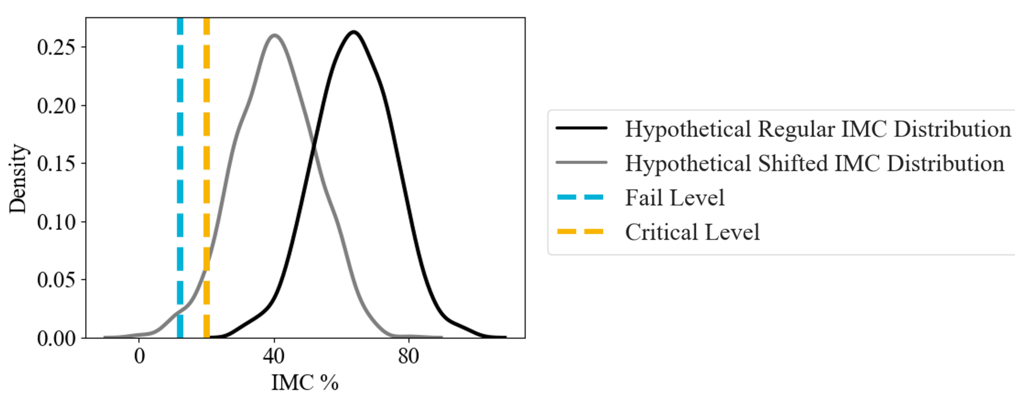


Figure 3: Hypothetical IMC process performance distribution.

2.2 Root Cause

NSOP events can have many root causes. A possible issue that could occur is that a layer of oxidation could form around the bond ball when it is exposed to oxygen or moisture right after forming the FAB, which makes it harder to bond it to the bond pad. Forming gas can protect the bond ball against oxidation and thus ensure proper wire bonding. However, problems with this forming gas could lead to low IMC coverages and thus to potential NSOP events. Forming gas as root cause can manifest itself in several ways, but we will focus on two in this paper. First, in case the forming gas flow rate is too low, it is possible that not sufficient protection is given. Second, the forming gas can be disrupted by the diffuser flow. The diffuser flow has the purpose to protect the lens, which is needed for accurate wire bonding, from heat flows. Mimicking the problems related to the forming gas flow rate and the diffuser flow rate with experiments gives us the opportunity to find wire bond machine-signal-related features that we can directly link to the problems by comparing them to machine-signal-related features collected under regular IC wire bonding conditions.

2.3 Literature

Root cause analysis (RCA) of the semiconductor manufacturing process is considered to be challenging (Rokach and Hutter 2012) as it is time-consuming and labor intensive. Moreover, Papageorgiou et al. (2022) indicate that the major drawback of traditional RCA methodologies is a lack of using the information hidden in the data collected in manufacturing processes nowadays. Technologies such as machine learning and deep learning can play an important role in identifying this information and transforming it into knowledge. Psarommatis et al. (2022) discuss the concept of ZDM as approach to use these type of advanced technologies to improve both process and product quality by reducing defects and ensuring that failed products do not leave the manufacturing site.

e Oliveira et al. (2023) present an overview of Automatic Root Cause Analysis (ARCA) solutions that are developed in different manufacturing environments. In ARCA, techniques such as data mining and machine learning are used to make the root cause analysis process more efficient. The authors identified 13 papers that focus on developing such solutions for the semiconductor industry. One of the dimensions compared is how the root causes are actually extracted from the models. The authors observed that the identified papers only link factors to a specific problem/fault and then extract the root causes, while none of the papers directly relate factors to the specific root cause. The explanation they give for this observation is that it is probably difficult to get data sets with the root causes. In this work, we collect a real-world data set from NXP Semiconductors N.V. by performing experiments mimicking a specific root cause to overcome that difficulty.

When focusing on quality detection and root cause analysis in wire bonding, we find several papers already addressing these topics. We can distinguish two different literature streams to find root causes in wire bonding. On the one hand, we find papers focusing on traditional RCA methodologies. For example, Sumagpang and Gomez (2018) use methodologies such as fishbone diagram, cause and effect diagram, and Why-Why Analysis to find potential root causes of NSOP events. On the other hand, we find papers focusing on using different sensing modalities to find root causes. Lim et al. (2011) investigate root causes of wire bond related failures using optical microscopy, secondary electron microscopy and transmission electron microscopy. Asghar et al. (2021) use focused ion beam and scanning electron microscopy to show the likely root causes of bond failure problems.

Compared to root cause analysis, it is more common for quality detection at wire bonding to use data-driven models. There are multiple papers focusing on building data-driven models studying images made for visual inspection to detect wire bonding defects (Perng et al. 2007; Chen et al. 2021; Zhan et al. 2023). As image-based quality detection can only be performed in hindsight, other researchers focus on studying real-time wire bond quality control using machine signals. For example, Feng et al. (2021) propose a time-frequency analysis using the bonding voltage and current signals to detect failures.

However, Al-Baddai et al. (2021) indicate that the long-term goal is not only to detect potential IC failure during wire bonding, but also the exact type of failure and especially directly link it to a root cause.

We observe that there is a gap in the literature where wire bonding quality detection is combined with automatic root cause analysis. Therefore, the novelty in our work is that we leverage the machine-signal-related features obtained from wire bond machines to directly find a root cause of a failure mode using data-driven models. To the best of our knowledge, we are the first in semiconductor wire bonding manufacturing to do this.

3 MODELING APPROACH

3.1 Experiments

A challenge with the NSOP failure mode is the low occurrence rate (Hew et al. 2022). As a consequence, we face imbalanced datasets as it will take a lot of time before sufficient NSOP events are collected, which could be used to train the ML model. Therefore, we will perform experiments to mimic a known possible root cause that could lead to a near NSOP event and use it for training. In this way, we can link the machine-signal-related features directly to the potential root cause, which is in our case the forming gas. We will perform four experiments in which we focus on the problems as discussed in Section 2.2. The wire bond machine allows different values for both the forming gas flow rate and the diffuser flow rate, but in practice the values are always kept on the same level during wire bonding. We refer to these levels as the standard settings, which are the regular wire bond manufacturing conditions. During the experiments we will consider two settings for the forming gas flow rate and the diffuser flow rate, which are {Standard, Low} and {Standard, High}, respectively. We choose these settings, because a low forming gas flow rate could lead to lack of sufficient protection and a high diffuser flow rate could lead to disruption of the forming gas. The exact decreasing percentage and increasing percentage is chosen arbitrary, but within the limits of what is allowed by the wire bond machine. The experiment in which both settings are standard serves as reference for the other experiments. Each experiment will use a different combination of settings. Table 1 shows a summary of the experiments.

Table 1: Summary of experiments.

	Forming gas flow rate	Diffuser flow rate
Experiment 1	Standard	Standard
Experiment 2	Low	Standard
Experiment 3	Standard	High
Experiment 4	Low	High

3.2 Data Description and Preparation

In this study, we focus on experimental data collected with commercial wire bond machine software from a particular bond recipe and wire bond machine measured on one day. The reason for this is that in a pre-study, we found that significant shifts over time take place and observed significant differences per wire bond machine. This causes noise in the data leading to poor prediction results. Therefore, we filtered out this noise in order to find features related to machine signals that are relevant in finding the root cause that could lead to potential NSOP events.

The dataset contains machine signal information regarding the four performed experiments. Each experiment contains 44 ICs, which means that the entire dataset contains 176 ICs. The initial dataset contains 77 features, 43 of which are related to machine signals. It is important to mention that the machine signals are aggregated, which means that they are only available on device level. Due to confidentiality reasons we anonymize the names of the features in this paper.

As our goal is to link machine-signal-related features to the described root cause, we only consider these features related to machine signals and discard the others. We further reduce the feature set by discarding features that are not available for every IC or have no variance. In case it is possible, we extract additional features by calculating the coefficient of variation. After performing these data pre-processing steps, 39 machine-signal-related features are available.

3.3 Classification Model

We will use a binary classification model to find relevant machine-signal-related features that link to the forming gas root cause (see Section 2.2). This root cause is imitated with the performed experiments (see Section 3.1). The idea is that if we are able to predict whether ICs come from the reference experiment (experiment 1) or from either experiment 2, 3 or 4, then this would indicate that the underlying behavior of one or more features is different between these experiments. Learning these machine-signal-related features and the different behavior is important, because this would give opportunities to be able to recognize near NSOP events already during the wire bond manufacturing process and thus will prevent these from occurring in the field.

We adopt a Random Forest (RF) classification model because RF was able to generate the best results in our pre-study for a similar problem setting compared to other binary classification models. The data set is randomly divided into a train set (75%) and a test set (25%). To gain reliable results, we run the model 1000 times all with different initial seeds. According to Zhu et al. (2022) there are seven main hyperparameters that should be considered when building a RF model. Table 2 shows the hyperparameter values that we use in our RF model. We choose these values because they are the default values in the scikit-learn Python module version 1.4.0. (Pedregosa et al. 2011), which we use to build the RF classification model.

Table 2: RF hyperparameter values.

Hyperparameter	Value
Number of estimators	100
Criterion	gini
Maximum depth	None
Number of node splitting	2
Node size	1
Maximum features	sqrt (squared root of number of features)
Bootstrap	True

We will build three different RF classification models. In each model, we will compare the reference experiment (experiment 1) with one of the root cause experiments (experiment 2, 3, or 4). Therefore, each model contains two different groups, which we will refer to as group 1 and group 2. In all three models experiment 1 represents group 1 and one of the root cause experiments represents group 2. We want to successfully predict whether an IC comes either from group 1 or group 2 and find the features that are important to do this as our goal in this work is to determine the relevant machine-signal-related features that link to the root cause. Therefore, we determine the feature importance of the RF classification model using permutation importance as originally proposed by Breiman (2001). A feature is considered to be important when it has an importance value above zero, since the feature then has a positive effect on the overall prediction accuracy. The feature importance is determined by randomly permuting the values of each feature and calculating the corresponding performance difference of the model. We will remove features when they are smaller or equal to zero and run the model again with the remaining features. We will repeat this until all values are above zero. Table 3 shows a summary of the three different RF classification models and their corresponding groups.

Table 3: Summary of RF classification models.

	Group 1	Group 2
Model 1	Experiment 1	Experiment 2
Model 2	Experiment 1	Experiment 3
Model 3	Experiment 1	Experiment 4

We will compare the machine-signal-related features of the final models with each other and look for features that are important in each model. Thereafter, we will only consider these features and use a K-Nearest Neighbour (KNN) model to look for clusters, which we can relate to the different experiments. The idea behind this is that we first want to identify relevant machine-signal-related features which we can link to the forming gas root cause, and then want to see if we are also able to differentiate between the forming gas flow rate issue and diffuser flow rate issue. We again randomly divide the data set into a train set (75%) and a test set (25%) and run the model 1000 times with different initial seeds for reliable results. The most crucial hyperparameter in a KNN model is the number of considered neighbours (Yang and Shami 2020), which we choose to be equal to five. We choose this value because it is the default value in the scikit-learn Python module version 1.4.0. (Pedregosa et al. 2011), which we use to build the KNN model.

3.4 Model Evaluation

To evaluate the performance of the binary classification model we use three different metrics. The accuracy metric, which is calculated by $\frac{\textit{Correct number of classifications}}{\textit{Total number of classifications}}$, represents the total amount of correctly predicted ICs from both group 1 and group 2. The precision metric, which is calculated by $\frac{TP}{TP+FP}$, represents the amount of ICs that are correctly predicted to come from group 2 out of all the ICs that are predicted to come from group 2. The recall metric, which is calculated by $\frac{TP}{TP+FN}$, represents how many ICs are correctly predicted to come from group 2 out of all the ICs that actually come from group 2. In these formulas TP, TN, FP, and FN are abbreviations for True Positive, True Negative, False Positive, and False Negative, respectively. In our case, true positives are ICs correctly predicted as group 2 and true negatives are ICs correctly predicted as group 1. We consider recall to be the most important metric, because the higher the recall the better the classification model is able to predict ICs coming from group 2. This is important as the costs of missing one near NSOP event are much higher than the costs of performing additional analysis on an IC that actually turns out to be of good quality.

To evaluate the performance of the KNN model we only use the accuracy metric. In our KNN model, the accuracy represents the total number of correctly classified ICs as either experiment 2, 3, or 4, compared to the total number of classified ICs.

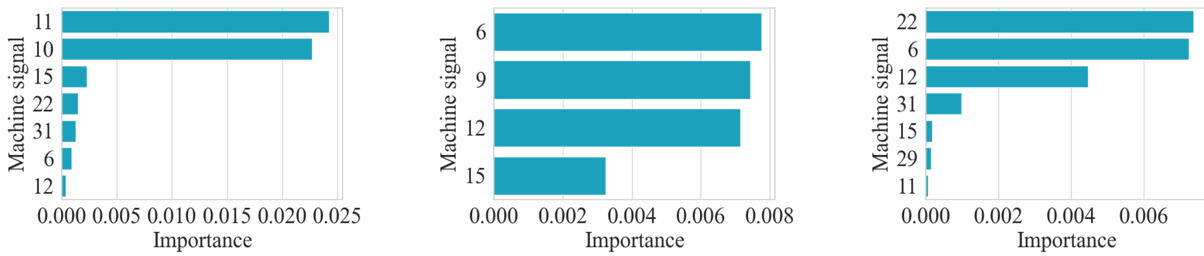
4 RESULTS

Table 4 shows the evaluation results, including their 95% confidence intervals, of the three final RF models. These are the models in which none of the features are below or equal to zero anymore. For all final models we find very good results for all three evaluation metrics as they are all above 0.98. This means that all RF binary classification models are able to differentiate well between the reference experiment (group 1) and the experiment in which one (experiment 2 and 3) or two (experiment 4) settings are changed.

Figure 4 shows the feature importance of the used features as predictors of the final models. We observe that multiple features are important in the different classification models, but we find three machine-signal-related features that are important in each model. These are features 6, 12, and 15. Further, we also see that features 11, 22, and 31 are important predictors for both model 1 and model 3. These are the models considering experiment 2 and 4 in which the common denominator is that the setting of the forming gas flow rate is put on low.

Table 4: Evaluation results of final RF models.

	Accuracy	Precision	Recall
Model 1	0.992 (0.990; 0.993)	0.989 (0.987; 0.991)	0.994 (0.993; 0.996)
Model 2	0.996 (0.995; 0.997)	0.994 (0.992; 0.996)	0.998 (0.997; 0.999)
Model 3	0.989 (0.987; 0.991)	0.984 (0.980; 0.988)	0.993 (0.991; 0.995)



(a) Model 1 (b) Model 2 (c) Model 3

Figure 4: Machine-signal-related feature importance plots.

Because our RF classification models are capable of differentiating between the reference experiment and the root cause experiments, we are able to recognize situations in which potential NSOP events can occur due to problems with the forming gas. We argue that machine-signal-related features 6, 12, and 15 are valid indicators for the forming gas as root cause, since we find these signals to be important in all three models. These insights are relevant as these could speed-up root cause analysis in case of quality incidents related to an NSOP. Furthermore, monitoring these machine-signal-related features more closely during regular wire bonding manufacturing could help in proactively detecting suspicious situations in which forming gas issues could lead to potential NSOP events.

Although we can link the aforementioned machine-signal-related features to the forming gas flow root cause, there are still different problems that can cause this. Therefore, we want to find out if we can link the machine-signal-related features to situations raised in the experiments 2, 3, and 4. Figure 5 shows a 3D scatterplot of features 6, 12, and 15 in which we make a distinction between the three different experiment groups. We observe that clusters of the three experiments can be visually distinguished. Using a KNN model we are able to validate this observation as we find an accuracy of 0.738 (0.734; 0.742). This means that we can not only link the machine-signal-related features to forming gas as root cause, but also in many cases to the corresponding problem that caused the forming gas issue. Morever, we only need 3 features out of the initial 39, which is important information for wire bond operators and quality engineers as they only have to focus on these three features when considering gas flow as root cause.

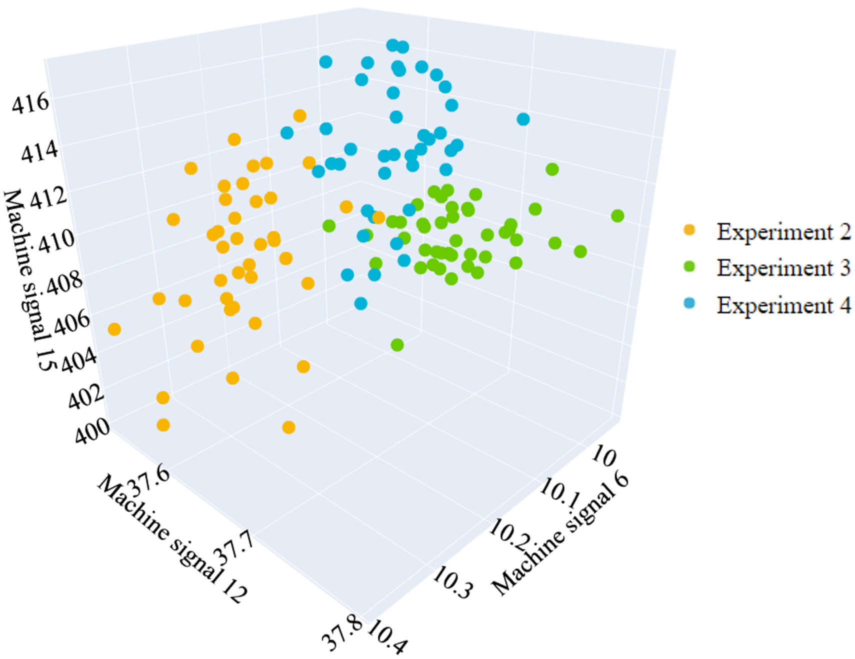


Figure 5: 3D scatterplot comparing machine-signal-related features 6, 12, and 15 between the different root cause experiments.

5 DISCUSSION

In this work, we propose a data-driven solution to use machine-signal-related features for quality detection and combine it with automatic root cause analysis of failure modes in a wire bonding manufacturing setting. To the best of our knowledge, we are the first in semiconductor wire bonding that focuses on this problem. Although, literature exists on using machine signals to detect wire bond quality, no studies are known that directly link machine signals to the root causes of potential failures.

As part of our method, we perform experiments to mimic problems that could lead to the forming gas as root cause of (near) NSOP events and to overcome challenges with imbalanced datasets due to the low occurence rate of these events. We also perform an experiment under regular wire bond conditions that serves as reference, so that actual comparison with the other experiments is possible. We use a RF classification model to differentiate between experiments under regular and changed wire bond settings as in our pre-study for a similar problem setting was found that RF was able to generate best results compared to other binary classification models. In general, our method can be used in problem contexts similar to the one described in this paper, not only limited to the semiconductor industry, when linking machine-signal-related features to a root cause of a failure mode.

Our results are based on real-world data from a use case at NXP Semiconductors N.V.'s back-end fab in Kuala Lumpur, Malaysia. For our proof of concept, we focused on a single bond recipe, single wire bond machine, single failure mode, and one corresponding root cause. Our results show that it is possible to directly link machine-signal-related features to root causes, and therefore similar analysis can be performed for other bond recipes, wire bond machines, failure modes, and root causes. To use the proposed data-driven solution during real-time wire bond manufacturing it is important that it can be deployed in the edge. However, the chosen time-frame of one day makes that at the moment the results are not yet ready to accomplish this as over time data characteristics can change, which need to be accounted for. Further, implementing our model into an actual manufacturing environment also involves other challenges such as determining how often the model should be retrained, using real-time data as it could be noisy or incomplete, and ensuring a proper data infrastructure.

6 MANAGERIAL IMPLICATIONS

Leveraging machine signal data from wire bond machines and link them to root causes of failure modes will enable to gain more real-time quality control. This will help reducing the number of failures occurring in the field, which will save labor hours and costs. Further, it will contribute to higher yield realization as potential alarming situations leading to a higher risk of failure could be detected sooner. The operational decision-making regarding test sampling can also be improved. The reason for this is that in semiconductor manufacturing only limited test capacity is available, and therefore more efficient decisions can be taken when information about IC quality indications is available. Lastly, it provides knowledge regarding the importance of machine-signal-related features. In our work, we found that we only need 3 out of 39 machine-signal-related features to link forming gas issues to potential IC failure. This helps quality engineers in their task of finding the root cause of failures. Moreover, smarter cloud-storing decisions can be made when knowing which machine-signal-related features to focus on, which is important from a sustainability perspective.

7 CONCLUSIONS AND FUTURE WORK

In this paper, we showed that we are able to directly link wire bond machine-signal-related features to the forming gas as root cause of potential (near) NSOP events. We performed experiments to mimic known problems with the forming gas and using RF binary classification models we were successfully able to differentiate between the reference experiment with standard settings and the experiments in which we changed the setting for the forming gas flow rate and/or the diffuser flow rate. We found three relevant machine-signal-related features that are important in all three models and can be linked to the forming gas. Furthermore, we also concluded that the features in most cases could successfully distinguish to which forming gas issue the IC was related.

For future work, the current research should be extended and incorporate more bond recipes, wire bond machines, taking into account a longer time-window, and quality variation of the bond pad. Further, the performance of the RF binary classification model could be improved by tuning the hyperparameter values. As the results are promising more research should also be performed on how such a type of data-driven solution can be moved from the cloud to the edge, so that it can actually be used to improve wire bonding manufacturing quality detection and prevention. When moving it to the edge it would also be interesting to explore other tree-based bagging or boosting models next to the used RF model. Lastly, when bringing such a model into the actual manufacturing process also other challenges, such as the examples mentioned in Section 5, should be addressed.

ACKNOWLEDGMENTS

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REFERENCES

Al-Baddai, S., M. Juhrisch, J. Papadoudis, A. Renner, B. Lippmann, C. Luca, *et al*. 2021. “Automated Anomaly Detection Through Assembly and Packaging Process”. In *Artificial Intelligence for Digitising Industry – Applications*, edited by O. Vermesan, 161–176. New York: River Publishers https://doi.org/10.1201/9781003337232-14.

Alam, L. and N. Kehtarnavaz. 2022. “A Survey of Detection Methods for Die Attachment and Wire Bonding Defects in Integrated Circuit Manufacturing”. *IEEE Access* 10:83826–83840 https://doi.org/10.1109/ACCESS.2022.3197624.

Aryan, P., S. Sampath, and H. Sohn. 2018. "An Overview of Non-Destructive Testing Methods for Integrated Circuit Packaging Inspection". *Sensors* 18(7):1–27 https://doi.org/10.3390/s18071981.

Asghar, M. T., T. Frank, and F. Schwierz. 2021. "Failure Analysis of Wire Bonding on Strain Gauge Contact Pads Using FIB, SEM, and Elemental Mapping". *Engineering Proceedings* 6(1):1–4 https://doi.org/10.3390/I3S2021Dresden-10142.

Breiman, L. 2001. "Random Forests". *Machine Learning* 45:5–32.

Chen, J., Z. Zhang, and F. Wu. 2021. "A Data-Driven Method for Enhancing the Image-Based Automatic Inspection of IC Wire Bonding Defects". *International Journal of Production Research* 59(16):4779–4793 https://doi.org/10.1080/00207543.2020.1821928.

Chen-Fu Chien, Y.-S. L. and S.-K. Lin. 2020. "Deep Reinforcement Learning for Selecting Demand Forecast Models to Empower Industry 3.5 and an Empirical Study for a Semiconductor Component Distributor". *International Journal of Production Research* 58(9):2784–2804 https://doi.org/10.1080/00207543.2020.1733125.

Choorat, T. 2015. "Back-End Process Training: Wire Bonding". *NXP Semiconductors N.V.*.

Dah-Chuan Gong, Jia-Lun Kang, G. C. L. and T. C. Hou. 2017. "On an IC Wire Bonding Machine Production–Inventory Problem with Time Value of Money". *International Journal of Production Research* 55(9):2431–2453 https://doi.org/10.1080/00207543.2016.1213914.

e Oliveira, E., V. Miguéis, and J. Borges. 2023. "Automatic Root Cause Analysis in Manufacturing: an Overview Conceptualization". *Journal of Intelligent Manufacturing* 34:2061–2078 https://doi.org/10.1007/s10845-022-01914-3.

Espadinha-Cruz, P., R. Godina, and E. M. G. Rodrigues. 2021. "A Review of Data Mining Applications in Semiconductor Manufacturing". *Processes* 9(2):1–38 https://doi.org/10.3390/pr9020305.

Feng, W., X. Chen, C. Wang, and Y. Shi. 2021. "Application Research on the Time–Frequency Analysis Method in the Quality Detection of Ultrasonic Wire Bonding". *International Journal of Distributed Sensor Networks* 17(5):1–11.

Hew, B. H., K. W. Lim, Y. Sun, Y. B. Wang and J. K. Y. Song. 2022. "Improving Wirebonding Failure Classification Across Bond Recipe via Machine Learning". In *2022 IEEE 24th Electronics Packaging Technology Conference (EPTC)*, 854–857 https://doi.org/10.1109/EPTC56328.2022.10013249.

Lim, H. K., Y. Kim, and M.-K. Kim. 2017. "Failure Prediction Using Sequential Pattern Mining in the Wire Bonding Process". *IEEE Transactions on Semiconductor Manufacturing* 30(3):285–292 https://doi.org/10.1109/TSM.2017.2721820.

Lim, Y. K., S. Yuan, J. B. Tan, A. Yeo, Y. N. Hua, N. R. Rao *et al*. 2011. "Wire Bonding, Bumping & Assembly Related Failures Improvements". In *18th IEEE International Symposium on the Physical and Failure Analysis of Integrated Circuits (IPFA)*, 1–5 https://doi.org/10.1109/IPFA.2011.5992798.

Papageorgiou, K., T. Theodosiou, A. Rapti, E. I. Papageorgiou, N. Dimitriou, D. Tzovaras *et al*. 2022. "A Systematic Review on Machine Learning Methods for Root Cause Analysis Towards Zero-Defect Manufacturing". *Frontiers in Manufacturing Technology* 2:1–16 https://doi.org/10.3389/fmtec.2022.972712.

Pedregosa, F., G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel *et al*. 2011. "Scikit-learn: Machine Learning in Python". *Journal of Machine Learning Research* 12:2825–2830.

Perng, D.-B., C.-C. Chou, and S.-M. Lee. 2007. "Design and Development of a New Machine Vision Wire Bonding Inspection System". *The International Journal of Advanced Manufacturing Technology* 34:323–334.

Psarommatis, F., J. Sousa, J. P. Mendonça, and D. Kiritsis. 2022. "Zero-Defect Manufacturing the Approach for Higher Manufacturing Sustainability in the Era of Industry 4.0: a Position Paper". *International Journal of Production Research* 60(1):73–91 https://doi.org/10.1080/00207543.2021.1987551.

Rokach, L. and D. Hutter. 2012, 10. "Automatic Discovery of the Root Causes for Quality Drift in High Dimensionality Manufacturing Processes". *Journal of Intelligent Manufacturing* 23:1915–1930 https://doi.org/10.1007/s10845-011-0517-5.

Rooney, D. T., D. Nager, D. Geiger, and D. Shanguan. 2005. "Evaluation of Wire Bonding Performance, Process Conditions, and Metallurgical Integrity of Chip on Board Wire Bonds". *Microelectronics Reliability* 45(2):379–390 https://doi.org/https://doi.org/10.1016/j.microrel.2004.06.008.

Sumagpang, A. R. and F. R. I. Gomez. 2018. "Chip-On-Lead Semiconductor Package with Copper Wirebonding". *International Research Journal of Advanced Engineering and Science* 3(4):281–289.

Wang, C. and R. Sun. 2009. "The Quality Test of Wire Bonding". *Mathematical Models and Methods in Applied Sciences* 3:50.

Yang, L. and A. Shami. 2020. "On Hyperparameter Optimization of Machine Learning Algorithms: Theory and Practice". *Neurocomputing* 415:295–316 https://doi.org/https://doi.org/10.1016/j.neucom.2020.07.061.

Zachariasse, F., G. O'Halloran, A. IJzerloo, and R. Rongen. 2013. "Planar Analysis of Copper-Aluminium Intermetallics". In *Conference Proceedings from the 39th International Symposium for Testing and Failure Analysis*. November 3rd-7th, San Jose, California, USA, 297-300 https://doi.org/10.31399/asm.cp.istfa2013p0297.

Zhan, D., J. Lin, X. Yang, R. Huang, K. Yi, M. Liu *et al*. 2023. "A Lightweight Method for Detecting IC Wire Bonding Defects in X-ray Images". *Micromachines* 14(6):1–18 https://doi.org/10.3390/mi14061119.

Zhu, N., C. Zhu, L. Zhou, Y. Zhu and X. Zhang. 2022. "Optimization of the Random Forest Hyperparameters for Power Industrial Control Systems Intrusion Detection Using an Improved Grid Search Algorithm". *Applied Sciences* 12(20):1–16 https://doi.org/10.3390/app122010456.

AUTHOR BIOGRAPHIES

KENNETH J. BRAAKMAN is a doctoral candidate in the Department of Total Quality Operations at NXP Semiconductors N.V. and in the Department of Industrial Engineering and Innovation Sciences at the Eindhoven University of Technology. He obtained his master's degree in Operations Management & Logistics at the Eindhoven University of Technology cum laude. His primary research interest is in the area of modeling, controlling and optimizing high-tech manufacturing systems with a focus on product and process quality. His email address is kenneth.braakman@nxp.com.

D. MARTIN KNOTTER received his Ph.D. in Organometallic Chemistry at the University of Utrecht and worked 10 years in Philips Research Laboratories on surface chemistry and Semiconductor processing. It included an assignment to IMEC (Leuven, B) on ultraclean processing. The impact and analysis of contamination became the topic in NXP Semiconductor N.V. years that resulted in becoming 6-sigma problem solver on everything related to contamination having impact on process performance in Front End and Back End semiconductor processes. His email address is martin.knotter@nxp.com.

ALP AKCAY is an Associate Professor in the Department of Industrial Engineering and Innovation Sciences at Eindhoven University of Technology. He received his Ph.D. in Operations Management and Manufacturing from Carnegie Mellon University. His research interests include data-driven decision making under uncertainty with a particular focus on semiconductor manufacturing systems and supply chains. He is a core member of the AI-enabled Manufacturing and Maintenance lab of Eindhoven Artificial Intelligence Systems Institute (EAISI). His email address is a.e.akcay@tue.nl.

IVO ADAN is a Professor at the Department of Industrial Engineering of the Eindhoven University of Technology. His current research interests are in the modeling and design of manufacturing systems, warehousing systems and transportation systems, and more specifically, in the analysis of multi-dimensional Markov processes and queueing models. His email address is i.adan@tue.nl.