

A novel big data-driven framework for root cause analysis of in-line defects through Auto-Diagnostic

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Abstract: During wafer fabrication, the large volume of data related to process steps, equipment, and lot history are stored in databases for subsequent process monitoring and diagnosing potential faults. These data are pertinent in root-cause tracking when anomalies exist during the manufacturing process. However, root-cause tracking is often not a straightforward task as a variety of factors might be interrelated, and especially in the conventional troubleshooting process, it involves a lot of manual work and often requires the engineers' personal experience and domain knowledge. This paper presents a novel big data-driven framework of root cause analysis method through Auto-Diagnostic (AD). The Auto-Diagnostic framework consists of 3 innovative functionalities: an efficient way of data manipulation to form useful data frames for correlation results of all the potential root causes; an integrated system based on the special domain knowledge to provide the analysis that is close to real-time and daily diagnostic reports; a meaningful feedback system to train the whole framework using past lessons provided by subject matter experts. This approach has been validated to detect root causes of excursion with a stable accuracy of 70%. It has captured 16 win cases in recent 6 months and 80% of wins are from extremely tough cases with more than 800 steps and nearly impossible for engineers to troubleshoot.

Index Terms: Auto-Diagnostic, diagnostic, root cause, analysis

I. INTRODUCTION

Semiconductor manufacturing is one of the most complex manufacturing systems that contain hundreds to thousands of process steps. Economies of speed are critical as semiconductor products in consumer electronics era compete with increasingly shortening time-to-market [1]. The quality requirement becomes stricter year by year, and at the same time, the lifecycle of a single product is getting shorter. Therefore, process stability is critical for products that run with mass production and it has a large impact on company earnings.

Historically, Statistical Process Control (SPC) charts have been an indispensable statistical tool to help in the timely process monitoring and detection of the out-of-control (OOC) event due to deviation in a process or equipment. It is a plot of the data over time with three additional lines: the center line (usually the mean) and upper and lower control limits (UCL and LCL) [2], as shown in Fig. 1. If a data point falls outside the control limits as an OOC point, the process is said to be out-of-control and that an investigation is warranted to find and remove the causes. In semiconductor manufacturing, the SPC data consists mainly of in-line measurements readings collected from wafers during and after the completion of the process step.

Although SPC is helpful in detecting process drifts, there is a significant delay between the occurrence of drift and the resulting control chart violation. As production volume increases, faster response to process drift becomes necessary in order to assure high product quality and low cost. As such, rapid root cause analysis for an OOC event become significantly important to identify the source of problems and generate solutions.

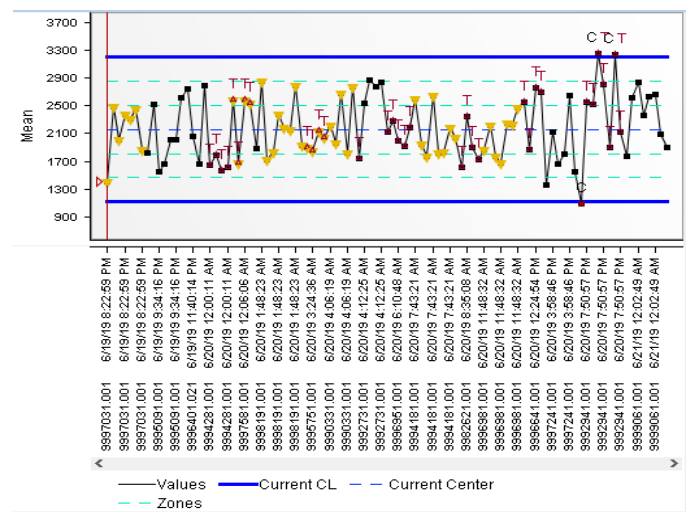


Fig. 1. An SPC chart example with UCL and LCL.

Currently, in Micron's front-end fabs, PEE (Process and Equipment Engineering) and RDA (Real-Time Defect Analysis) shift engineers are using Electronic Corrective Action Plan (eCAP) to response to SPC violations and monitor the in-line defects' performance. Upon the OOC event triggered by eCAP alert, engineers have to diagnose the OOC chart by checking on the chart's trend, extract the related defect metric and processing information, and then performing the commonality check for the OOC wafers. The current diagnosis practice has a few disadvantages:

- Poor effectiveness. Engineers need to manually select the related metrics and processing data to retrieve from the database. After that, engineers need to screen through all the plots to find out the source of the problem. The process is rather manual, subject to individual experiences and domain knowledge to detect the root cause, and thus highly prone to delay in reaction.

- Poor efficiency. The process is relatively time and resource consuming. Engineers need to know what are the parameters required at the start, because if there has any parameter missed out or required to extend the levels of troubleshooting, then will need to re-query the data again. Besides that, the time taken to diagnose a chart can be even longer when the data required to retrieve and analyze is huge or the analyzing software is hanged. Moreover, the process of advanced nanotechnology nodes becomes increasingly complicated to make the root cause tracking exponentially difficult and often not a straightforward task.

In this paper, we present an advanced big data-driven framework called Auto-Diagnostic (AD) to provide automated root cause analysis for OOCs in SPC charts to arrive the potential root causes of deviation. OOC charts are first filtered by a few criteria based on our triggering rule, then an innovative way of data manipulation is used to form useful data frames for correlation results of all the potential root causes. The whole analytics also includes domain knowledge checking and feedback system to train AD using past learned lessons provided by subject matter experts, etc. Upon completed the diagnosis, AD will generate meaningful reports to tabulate the potential root causes with plots and tables for illustration.

A detailed methodology is explained and discussed in the later sections to better illustrate the usefulness of the proposed approach. Section II explains the detailed flow and logic in AD. Section III proposes how to maintain important data libraries to support further data modeling and root cause analysis. Section IV introduces AD report content with plots and tables. Section V presents the system architecture of the entire end-to-end application in Hadoop. Section VI discusses the root cause analysis results and wins. Finally, our conclusion and future research directions are presented in Section VII.

II. METHODOLOGY

Our approach first judges OOC charts and will only process further root cause analysis for those charts satisfied a few criteria set in our triggering rule, then applies data manipulation and the whole analytics with 2 rounds of ranking including domain knowledge checking, past learned lessons provided by subject matter experts, time-weighted correlation and curve trending detection to reduce false alarms, etc.

A. Triggering Rule

As mentioned earlier, OOC charts are set upper control limits (UCL) and lower control limits (LCL). Those points beyond UCL or LCL are considered as OOC points inside the charts. To analyze a chart, it makes sense that this chart should have a minimum of 1 point within 24 hours and a minimum of 2 OOC points and 2 normal points in last 30

days since the whole analysis needs enough sample data to perform and narrow down the final potential root causes of OOC points.

B. Data Manipulation

The root causes of OOC points are possible to come from process equipment highly due to preventive maintenance (PM) and corrective maintenance (CM), process chambers, recipes, special work request (SWR), quality deviation report (QDR), lot attributes, reticle and resist during the photo process steps, etc. Since root cause resources are numerous and the data structures are increasingly complicated, an efficient approach is proposed to form a time-saving dataframe for nearly real-time root cause detection. A staging example of QDR dataset is shown in Table I. Different root cause datasets might have minor difference but with almost the same format as follows,

Table I
QDR Dataset Example

lot ID	wafer ID	QDR	Affected Step
9395201.001	NA	No	4200-28 WO ARC DEP, 4610-28 W1 MLR COAT, 3010-63 VIA PHOTO, 3010-68 VIA PHOTO, 4610-29 W2 MLR COAT
			4610-29 W2 MLR COAT, 3010-22 PILLAR PHOTO
9395201.001	5201-21	No	5030-55 BL AG OXIDE DRY ETCH, 3010-44 METCON PHOTO
9354791.001	NA	Yes	5030-55 BL AG OXIDE DRY ETCH
9354791.001	4791-09	Yes	

Data manipulation first queries all the potential root causes based on categories and merge them together with step name from different datasets and then form an efficient data frame.

First, a data ETL (extract, transform, load) step is invoked to query all the potential root causes as mentioned earlier and OOC chart data together. Then the root causes of different categories including lot/wafer IDs and the potential root cause itself are formed as vertical columns one by one, as shown in Table II. At the same time, lot and wafer IDs, measurement steps and process steps are tied to all the points in OOC charts. Such information is organized as another 3 columns (Table III). Finally, two sub-dataframes are inner joint together based on the same lot/wafer IDs, as depicted in Table IV. Root cause candidate 1 has higher possibility to be the real root cause because of the higher correlation and the exact same trend variation with Column OOC.

Table II
Dataframe Example of Potential Root Causes

lot ID	wafer ID	Root cause candidate 1	Root cause candidate 2
lot 1	wafer 1	0	1
lot 2	wafer 2	1	1

lot 3	wafer 3	0	1
lot 4	wafer 4	1	0
lot 5	wafer 5	0	0
lot 6	wafer 6	1	0

Table III
Dataframe Example of OOC Charts

lot ID	wafer ID	OOC label
lot 1	wafer 1	0
lot 2	wafer 2	1
lot 3	wafer 3	0
lot 4	wafer 4	1
lot 5	wafer 5	0
lot 6	wafer 6	1

Table IV
Final Dataframe Example after Data ETL

lot ID	wafer ID	OOC	Root cause candidate 1	Root cause candidate 2
lot 1	wafer 1	0	0	1
lot 2	wafer 2	1	1	1
lot 3	wafer 3	0	0	1
lot 4	wafer 4	1	1	0
lot 5	wafer 5	0	0	0
lot 6	wafer 6	1	1	0

C. The 1st Round of Ranking

The core idea is to rank all the columns representing all the potential root causes and select the most possible ones according to the correlation results. However, it is totally not enough if only relying on correlation values. We invoke several innovative ideas to make the rank number more accurate such as adding time-weighted correlation, domain knowledge checking, past learned lessons, and PM/CM checking to boost up the confidence of process equipment as real root causes.

1) Time-weighted correlation

Time-weighted correlation defines the recent OOC points to have higher possibilities and weights to contribute to the rankings, which is also a common sense for shift engineers' manual diagnostic. Rank numbers are calculated like regular correlation but with using weighted means based on time series. Weighted means can be calculated as in (1),

$$m_X = \frac{\sum_i w_i x_i}{\sum_i w_i}, m_Y = \frac{\sum_i w_i y_i}{\sum_i w_i}, \quad (1)$$

2) Domain knowledge checking

PEE and RDA shift engineers usually have their own domain knowledge based on individual troubleshooting experiences. For example, resist fails defects whereby the pattern is distorted, normally they will first suspect the photo or dry etch area.

There is a domain knowledge library including defect parameter, process step keywords, and corresponding suspicious loop range. Domain knowledge is converted as configuration settings in the source code to narrow down the suspicious steps. A config example shows as follows: if the defect parameter of OOC charts is CB_19_RESIDUE, current loop after PHOTO steps is with higher chance causing OOC. "ge" means greater and equal.

```
"CB_19_RESIDUE": {
  "step_key_words": "PHOTO$",
  "mode": "ge",
  "loop_range": "at_loop"}
```

3) Past learned lessons

AD will generate reports and embed report links in a dashboard for users' access and feedback collection. All the feedback will be stored in MSSQL. AD will query past feedback from MSSQL database of the same OOC chart and mark it in a report this time if available to avoid the wrong diagnostic repeatedly and remind users past root causes. A historical feedback example is shown in Table V.

Table V
Historical Feedback Example in AD Report

channel ID	session ID	actual root cause step	actual root cause type	actual root cause
235996_0	2019-04-28	3010-27 HV PHOTO	equipment id	PHVT7A7200
235996_0	2019-04-27	5030-27 HV NITRIDE DRY ETCH	process chamber id	APXT7A68C0

4) PM/CM checking

PM/CM checking is aimed to correlate OOC points and the lead lot after PM/CM to boost up the confidence on root cause findings since the first two lots got higher possibilities causing deviation after the equipment maintenance, even though this checking doesn't affect ranking numbers. The checking criteria are to use last OOC lot and check whether it is under the first two lots after certain PM/CM and certain step. For instance, we assume that such a dataframe is obtained after invoking PM/CM checking logic shown in Table VI. By given equipment id as APXTAABE00 and step as 5030-58 CHOP INSITU DRY ETCH, the first lead lot ID is 9335591.001, the 2nd lead lot is 9500431.001.

Table VI
PM/CM Checking Dataframe Example

equipment ID	context/lot ID	datetime	step name	ranking
APXTAABE00	WAIT_REPAIR	2018-10-14 15:46:00	null	7
APXTAABE00	9546341.001	2018-10-14 17:56:00	5030-08 ALIGN MARK INSITU DRY ETCH	8
APXTAABE00	9335591.001	2018-10-14 18:28:40	5030-58 CHOP INSITU DRY ETCH	9
APXTAABE00	9500431.001	2018-10-14 20:44:40	5030-58 CHOP INSITU DRY ETCH	10

D. The 2nd Round of Ranking

Although the 1st round of ranking does perform absolutely good accuracy, sometimes AD highlights obviously not true root causes due to a similar curve trend of commonality

checking in reports. The 2nd round of ranking helps reduce false alarms.

Assume a lot is going through hundreds of steps as shown in Fig. 2 and Tool B in Step 2 got issues inside causing deviation and OOC points in SPC chart when monitoring. Then the plotting trend of Tool A should be with a smooth curve and small variance and by contrast, Tool B's curve should have the trend beyond UCL or LCL and hit most of OOC points as depicted in Fig. 3.

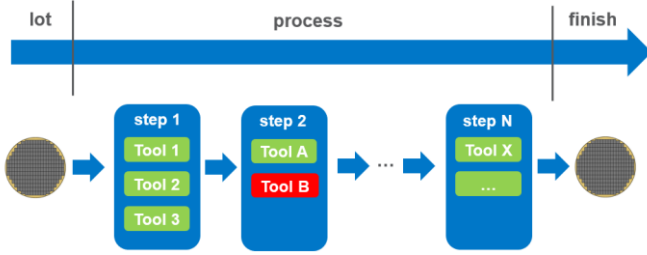


Fig. 2. Example of a lot processing structure.

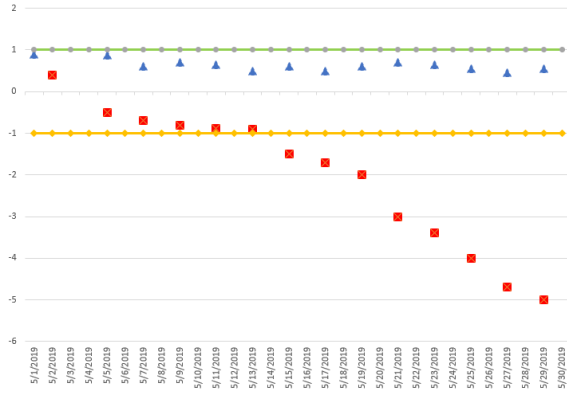


Fig. 3. Trend comparison between Tool A and Tool B.

A typical false alarm case is depicted in Fig. 4. The triangle points represent the measurement values of root cause diagnosed by AD and the square points represent another tool in the same step as Tool 1. Even Tool 1 obtained very high correlation values after the 1st round of ranking, it is a truly false alarm case since the plotting results of Tool 1 and Tool 2 are with a very similar trend in this process step meaning that there must be other tools from other steps causing the drifting trend and OOC points beyond LCL.

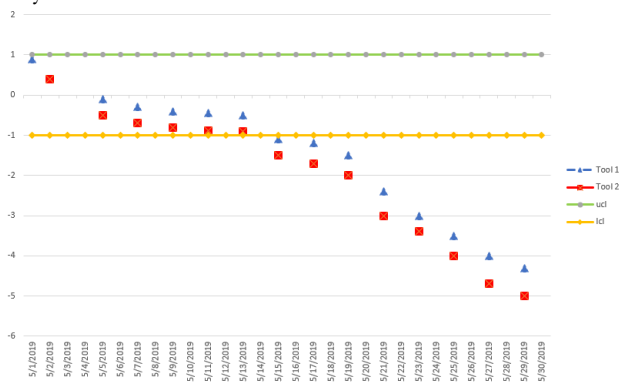


Fig. 4. A false alarm example.

Curve trend detection is invoked to filter out cases with a similar trend of plotting results in terms of the same step. We totally proposed 3 solutions of t-test, ARIMA and linear regression under scikit-learn and the final decision is to use linear regression. Based on the testing results, t-test only describes the variance of two different datasets using p-value which is not enough to determine the curve trending and it is not sensitive to time series analysis; ARIMA is good at time series forecasting but it will catch too detailed trend information, auto-tuning the parameters (p,d,q) also might pose a threat to the running time. P, d and q stand for the number of autoregressive terms, the number of nonseasonal differences needed for stationarity, and the number of lagged forecast errors in the prediction equation, respectively.

Our core idea using linear regression is to judge the slope difference of fitted curves and the percentage of OOC points from each curve for commonality checking. This solution needs a few parameters as configurations of trend detection algorithm such as the range of slope difference, upper and lower limitations of OOC percentage from curves representing all the instances in some step. Those parameters are learning and adjusted from Past Lesson Learnt Library stored all the past analysis results in MSSQL. Fig. 5 illustrates the proposed trend detection flow.

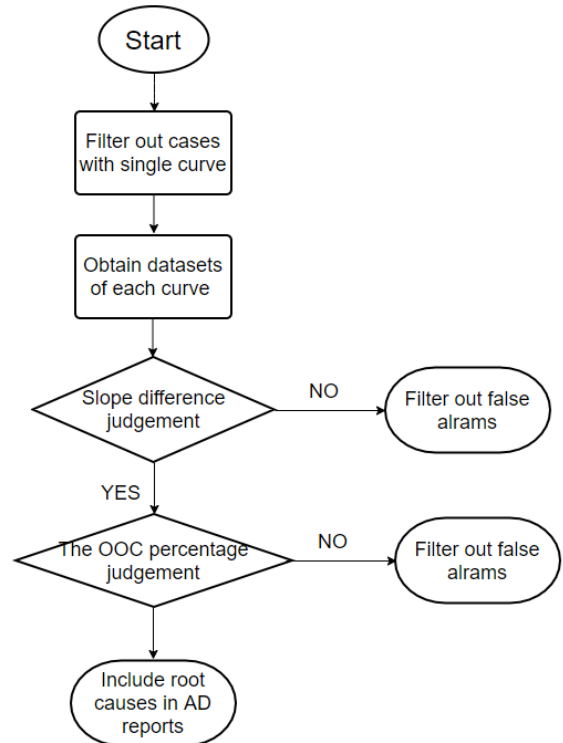


Fig. 5. Trend detection flow.

After filtering out false alarms as root cause analysis results, we re-rank several final remaining root causes considering the weight of commonality. The more recent OOC points hit, the higher correlation values and ranking numbers obtained for each potential root cause.

Curve trend detection definitely reduces many false alarms. A comparison of potential root causes provided by AD before and after the 2nd round of ranking is depicted in Table VII and Table VIII. Previously, AD provided 12 possible root causes in the diagnostic report. In terms of the same OOC chart, it only shows 3 rows after false alarm removal and the 3 corresponding plots are also meaningful without similar curve trend inside, resulting in efficiency improvement for shift engineers' review and accuracy improvement since re-ranking provides more fair ranking numbers to make the real root cause with a high enough correlation value to be shown in reports as well.

Table VII
Root Causes in AD Report before Curve Trend Detection

process step	step type	feature	context value	correlation
5030-2B W1 OXIDE DRY ETCH	process step	process id	2B_W1_OXIDE_ B16A_A1	0.58
5030-2B W1 OXIDE DRY ETCH	process step	recipe	A1L2BOX1A1	0.58
5030-2B W1 OXIDE DRY ETCH	process step	equipment id	L2EX7AA400	0.58
1220-2B W1 OXIDE DRY STRIP CLN SCATTER	measurement step	recipe	Recipe\B16A\B1 6A_2B_ACI_A2.x ml	0.58
1220-2B W1 OXIDE DRY STRIP CLN SCATTER	measurement step	process id	B16A_2B_W2_O XIDE_DRY_STRIP _CLN_SCATTER_ ATLAS	0.58
1220-2B W1 OXIDE DRY STRIP CLN SCATTER	measurement step	equipment id	NA2P7B0200	0.13
5430-2B W1 OXIDE DRY STRIP CLN	at loop	process id	SPIN_D-100 1HF- 12-5A-IPA	0.58
5430-2B W1 OXIDE DRY STRIP CLN	at loop	lot attribute	ZWPP2BSP- CLEANEVALUA	0.58
5430-2B W1 OXIDE DRY STRIP	at loop	process id	STRIP-O2_PSK- 455-155-4400W- HE	0.58
5430-11 GATE PRE OXIDATION CLN 4100-43	incoming	recipe	PRCA4_RR	0.85
PERIPH TIN DEP 6000-10	incoming	equipment id	TNTR7A2400	0.82
NWELL WELL ANG P IMPLANT	incoming	equipment id	IMHE7B1100	0.78

Table VIII
Root Causes in AD Report after Curve Trend Detection

process step	step type	feature	context value	correlation
5030-2B W1 OXIDE DRY ETCH	process step	process id	2B_W1_OXIDE_ B16A_A1	0.68
5030-2B W1 OXIDE DRY ETCH	process step	equipment id	L2EX7AA400	0.68
3010-15 N+ PHOTO	incoming	process id	B16A 15 N+ PHOTO 01ELIM RRC2	0.72

III. DATA LIBRARIES

RDA and PEE provide a domain knowledge library containing the defect parameters and the corresponding process step pattern. With defect parameter obtained from OOC charts, the library can be searched and then narrows down the suspicious steps to reduce the analysis time. This domain knowledge library serves a key role in AD and greatly improve overall accuracy and performance.

There is another library called Past Lesson Learnt Library stored in MSSQL to track all the feedback from RDA and PEE engineers. We maintain this library not only for avoiding the wrong diagnostic repeatedly and reminding users past root causes in terms of the same chart, but also build a golden dataset for future analysis enhancement and algorithm improvement.

IV. AD REPORT

AD will generate diagnostic reports and attach them into a tableau dashboard with plots and tables for RDA and PEE shift engineers' review.

The diagnostic reports include reference information as a header, an OOC chart plot, a historical feedback table, a result table with all the potential root causes, the corresponding plots of those root cause candidates and a feedback section at the end to let engineers fulfill their comments. The following figures illustrate the whole report content.

AD Report for Channel_name:
**1500-24 SGDP INSITU DRY STRIP CLN EBEAM
REVIEW/CB_36_HOLES**
Channel: **657064** CKC: **0** Chart Type: **Mean**
Reference OOC Lot Id: **9928551**, Wafer Id: **8551-08**

Fig. 6. AD report header.

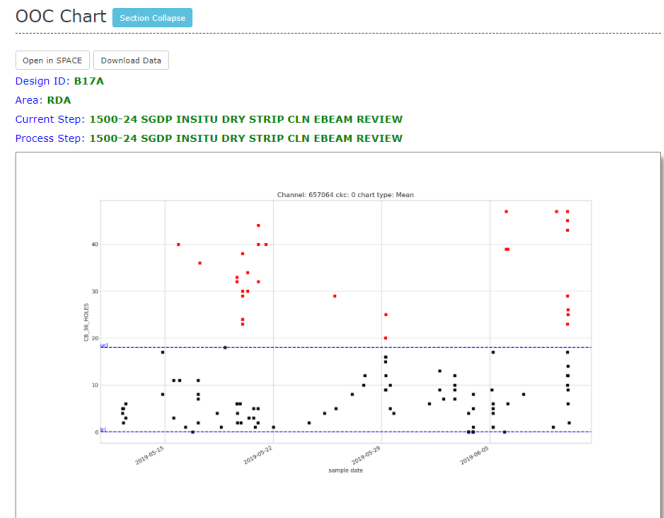


Fig. 7. OOC chart plot.

Fig. 6 and Fig. 7 depict the header and OOC chart plot in AD report. A historical feedback table and a result table

with 3 potential root causes are shown in Fig. 8 and Fig. 9, respectively. By clicking each root cause candidate, the corresponding boxplot chart and trend chart represented in Fig. 10, which is also the real root cause of deviations in this case. Finally, a feedback section at the end of AD report is illustrated in Fig. 11.

Historical Feedback

ch_id	session_id	actual_root_cause_step	actual_root_cause_type	actual_root_cause
657064_0	2019-05-29	3010-24 SGDP PHOTO	equipment_id	PHVTAVQA00
657064_0	2019-05-21	3010-24 SGDP PHOTO	equipment_id	PHVTAVQA00
657064_0	2019-05-20	3010-24 SGDP PHOTO	equipment_id	PHVTAVQA00
657064_0	2019-05-19	3010-24 SGDP PHOTO	equipment_id	PHVTAVQA00

Fig. 8. Historical feedback table.

Result Table

Show	All	entries	Search:	
mfg_process_step	step_type	feature	context_value	rank
4200-58 CHOP NITRIDE DEP	4_domain	equipment_id	MSPRAQEM00	1
4200-24 SGDP CARBON DEP	1_fmea	equipment_id	TCPRAREF00	2
4610-29 W2 MLR COAT	7_incoming	equipment_id	PHVTA1DHC0	3

Showing 1 to 3 of 3 entries

Previous 1 Next

Fig. 9. Result table with 3 root cause candidates.

Result Plots

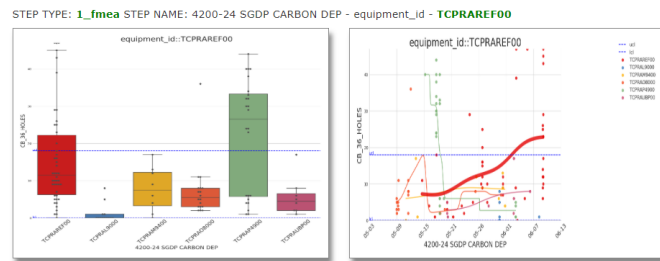


Fig. 10. The corresponding plots of root cause candidate “TCPRAREF00”.

Root Cause Feedback

Feedback Category:

☒ Root Cause Found
 ☐ Root Cause Not Found
 ☐ Root Cause Unknown

☐ Defect misclass/Recipe false count/Baseline issue

Micron Username: *

Input Your Micron Username

Flagged Root Cause *

4200-58 CHOP NITRIDE DEP::4_domain::equipment_id::MSPRAQEM00

Submit

Fig. 11. Feedback section.

V. AD AS A BIG DATA APPLICATION

AD currently is embedded in an end-to-end big data application. Refer to Fig. 6 for the system overview of the entire application.

The application is executed on a big data system named Hadoop. It includes ingesting raw datasets from Hive, Teradata and HBase, data ETL to form efficient data frames and root cause analysis to select the most possible ones based on ranking numbers and correlation results.

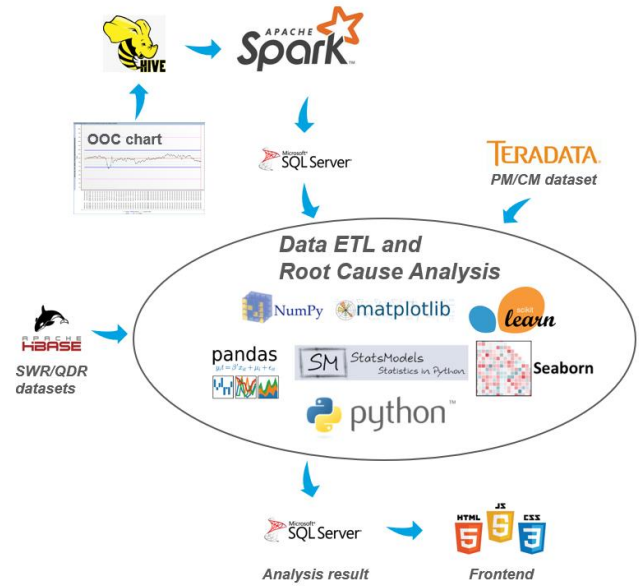


Fig. 6. The system architecture of AD as a Big Data Application.

VI. RESULTS AND WIN CASES

AD has been fully deployed in Feb 10 in the mid-July of 2018 with a tableau dashboard setup for RDA and PEE users to view frontend reports. In the same year, AD was deployed and integrated into the eCAP system in November of 2018 to provide a nearly real-time root cause analysis.

AD is used to diagnose all PEE charts and RDA review charts. In recent 6 months, 16 win cases have been reported in F10, among which, AD was able to pinpoint to the correct root cause with the analysis from lot start to hit step covered the machine, recipe, lot attribute, Special Work Request (SWR) and Quality Deviation Report (QDR) information. 80% of wins are from extremely tough cases with more than 800 steps and nearly impossible for humans to troubleshoot. The win cases are listed in Table VII.

Table VII
Auto-Diagnostic Win Cases

Step Name	Metric	Root Cause
B16A 3010-28 W0 PHOTO	CD1_LINE_BOT	1210-28 W0 PHOTO SEM CD – AV417BS400
B16A 1220-21 PILLAR INTEGRATED DRY STRIP CLN SCATTER	OCD	3010-21 PILLAR PHOTO – PHVTAC4200
N28A 1220-22 SGDP PRE POLY DEP 4 SCATTER	DEPTH_ARRAY_OXIDE_E DGE	4110-22 DHC POLY DEP – ZPIQMLMPBGM10POPOP
N18A 5200-59 PERIPH OXIDE CMP	THK_STACK_ARRAY_EDG E_WAVGL	5200-22 PILLA OXIDE BUFF CMP - QDR 66060610
B27A 1230-29 W2 METAL CMP THK	DELTA_THK_OXIDE_NAA A	5200-2B W1 METAL CMP – ZCMC2BSP300XGIII
N18A 1200-41 BITCON PHOTO REG	REG_Y	3010-22 PILLAR PHOTO – PHVTAVQL00
N18A 1230-22 PILLAR POLY DEP 2 THK	THK_POLY_NAAA_WAVG L	4110-22 PILLAR NITRIDE DEP 3 – KTRGAVJU00

B17A 1250-21 PILLAR POLY WET ETCH WEIGHT	DELTA_MASS_WAVGL	4200-21 PILLAR INSITU DEP – OPPRAD7600
B16A 1210-52 WL INSITU DRY STRIP CLN SEM CD	CD2_TIERSTOTIERS	3010-52 WL PHOTO - B16A_52_WL_PHOTO_WLMRR C_RETARGET
B16A 1210-57 CHOP INSITU DRY STRIP CLN SEM CD	CD3_57+54_EDGE_BOT_ PULLBACK	B16A 57 CHOP PHOTO F15RECIPE_PRETARGET
N18A 1250-21 PILLAR POLY WET ETCH WEIGHT	DELTA_MASS_WAVGL	SWR 4285910
8120-PV PST THK AL- FLM1 MEA	REFLECTIVITY_AL	8120-PV PST THK AL-FLM1 MEA - KSFAXA28200
B16A 1500-53 PERIPH OXIDATION EBEAM REVIEW	CB_42_VOID	4300-53 PERIPH WSIX SPUTTER – MMENAA1800
N18A 1500-55 BL METAL CMP EBEAM REVIEW	CB_51_BLOCKED_ETCH	4200-55 BL CARBON DEP – TCVXATAP30
B27B 1500-21 DHC POLY CMP EBEAM REVIEW	CB_33_CMP_SCRATCH	5200-45 SL OXIDE CMP – recipe B27B_45SL_OXIDE_22
B17A 1500-24 SGDP INSITU DRYSTRIP CLN EBEAM REVIEW	CB_36_HOLES	4200-24 SGDP CARBON DEP - TCPRAREF00

Besides that, a tableau dashboard was set up to track the weekly AD's performance. There are many improvements and enhancement work along the way to boost the diagnostic accuracy and user-friendliness, such as quantile check removal, domain knowledge checking and a feedback system to avoid past wrong diagnostic cases happened repeatedly. Based on available records from the dashboard, AD has been improved a lot and validated to detect root causes of excursion with a stable accuracy of 70%, as shown in Fig. 7.

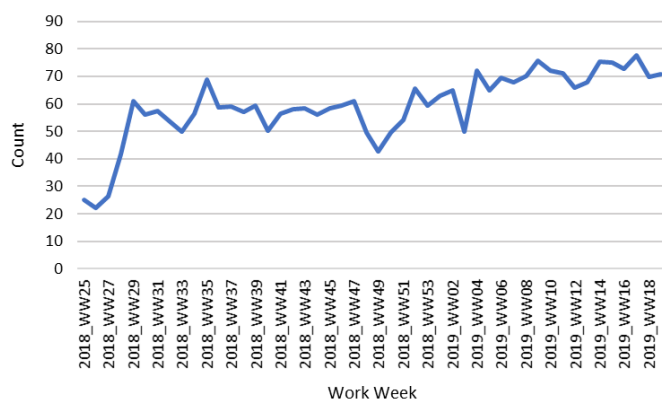


Fig. 7. Auto-Diagnostic accuracy from 2018-2019.

VII. CONCLUSION AND FUTURE WORK

Root cause analysis has been part of RDA and PEE engineers' daily routine work to monitor and improve process performance. In order to assure high product quality and low cost, a faster reaction to identify the source of problems and generate solutions for root causes of deviation becomes extremely important as production

volume increases. However, there has been no systematic way for root cause analysis of OOC points in SPC charts effectively and efficiently.

With the introduction of the big data application Auto-Diagnostic (AD) consisting of 3 innovative functionalities of an efficient way of data manipulation to form useful data frames for correlation results of all the potential root causes, an integrated system based on the special domain knowledge to provide the analysis that is close to real-time and daily diagnostic reports as well as a meaningful feedback system to train the whole framework using past lessons provided by subject matter experts, the troubleshooting efficiency of OOC charts has been improved a lot resulting in production yield improvement and man-hour saving. Usually, AD can assist those shift engineers to arrive at potential root causes within 20 mins instead of 4 hours by manual checking. This approach has been validated to detect root causes of excursion with a stable accuracy of 70%. It has captured 16 win cases in recent 6 months and 80% of wins are from extremely tough cases with more than 800 steps and nearly impossible for engineers to troubleshoot.

Future work includes worldwide fan-out deployment, machine learning using analysis result library to further improve the accuracy and more meaningful root cause diagnostics, data latency shortening and analysis time optimization.

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