ENABLING ZERO CHEMISTRY MAINTENANCE THRU A NOVEL UNIVERSAL ANALYZER POWERED BY E0DT NEURAL FRAMEWORK

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ABSTRACT

Achieving zero chemistry maintenance plays a competitive advantage to any industry including semiconductor manufacturing. Establishing critical controls thru novel tools and automation is the key towards lean and lights-out manufacturing.

The build-up of organics contaminants inherent to process limits chemistry efficiency and life. One known method of tracing organics in water industry is total organic carbon analysis or TOC. This method is limited to low conductive chemistry (<1 mS/cm²) from which application is not feasible to majority of semiconductor chemistries ($>2k \text{ mS/cm}^2$). This study developed a novel tool that enabled quantification of organics thru UV oxidation to form carbonic acid OC(OH)2 detectable thru conductive sensors. Powered by Gaussian Mixture Clustering for chemistry type profiling and Markov Modelling for organics speciation, the first to Industry analyzer standardizes chemistry life to organic carbon concentration ($\sigma^2 \leq 50$ ppm) with 99.98% organics real-time traceability. Based on the extrapolated datasets and chemistry dynamics, the concentration limits per conditions, parameter variations and internal states were predicted via ensembles of decision tree (EoDT) which unveils analyzer's universal use. Chemistry life in terms of organics concentration was prognosed using actual lab standard addition method producing 99.98% success rate from predicted value. From there, the universal analyzer was linked to automatic bleed and feed system to maintain desired concentration limit enabling zero chemistry maintenance - a new frontier in chemistry application relevant to fab, bump and assembly semiconductor manufacturing.

1.0 INTRODUCTION

Reduction of raw materials cost has been a constant challenge in any Manufacturing Industry. Seen on *Figure 1*, chemicals belong to top material cost from which Texas Instruments has always been dependent to third party manufacturers making our chemical spending almost uncontrollable.



Material cost allocation- 30% is from Chemical Maintenance

Multiple cost-reduction efforts have been launched to aggressively reduce cost of chemical consumptions in all Fab, Bump and Assembly sites highlighting one-of-a-kind innovations and thru sharing best known practices. One common solution is extension of chemical floor life defined in terms of total product count, parameter count, or timebased life. All of these monitoring is part of chemical maintenance to ensure integrity of process and product during manufacturing.

1.1 Chemistry Maintenance

Based on annual chemical consumption chemical or bath maintenance occupies 20-30% of total chemical spending. This large percentage of chemical cost is directly being dumped to waste treatment facilities once defined floor or production life was reached.

During bath maintenance, tool is being placed down state which contributes to 5-15% tool availability affecting tool throughput.

1.1.1 Chemistry Life Definition

Bath life or chemical floor life of was pre-defined by chemical supplier which is dependent of material or chemistry type (acid, solvent etc.) or process capabilities (yield, removal rate etc.). *Table 1* summarizes Texas Instruments known chemistry with their defined life. Low bath life value indicates high bath maintenance occurrence and high chemical cost.

PROCESS	CHEMISTRY	BATH LIFE	COUNT
FAB & BUMP	Plating 1	Demonster	А
	Plating 2	Parameter	В
	Plating 3	(Ampomin)	С
	Plating 4	Time	D
	Stripping 1	Count	Е
	Stripping 2	Count	F
	Flux 1	Time	G
ASSEMBLY	Deflash	Time	Н
	Rewash	Time	Ι
	Etch	Time	J
	Plating 5	Parameter	K
	_	(Amp∘dep)	

Table 1: Texas Instruments -Fab, Bump & AssemblyChemistry in their defined bath life

Chemistry life based on product or parameter count such as *Stripping 1* and *Stripping 2* chemistry (wafer count) and assembly *Plating 5* total current • deposition time (Amp.dep) were based on the maximum saturation point of base chemistry due to buildup of impurities from continues loading of products.

Chemistry life based on production floor time and staging such as assembly deflash chemistry and rewash chemicals (months) are due to chemistry degradation upon continues exposure to extreme manufacturing conditions such as heating and chemistry side-reactions.

Any ageing chemistry or bath are known to have lower process efficiency affecting product quality hence must be controlled and monitored during bath life extension.

1.1.2 Risk of Ageing Bath

Known risk of extending bath life are quality issues relating to low chemistry and process efficiency. Based on compile Failure mode and effect analysis (FMEA), more than 100 documented fail modes across areas directly pointing to ageing chemistry as potential root cause of failure. This includes critical customer issues such as voiding generation from ageing wafer plating bath, non-wets due to non-uniform plate relating to ageing plating bath and die crack from lead frame non-plate issue relating to ageing etch chemical life as shown in *Figure 2*.



Customer Issue- die crack due to voiding processed in aged bath

Bath life controls established for all chemistry thru tool setup and automation watchdogs. For any spike of quality issues nearing bath life, one known action is to further tighten bath maintenance and frequency resulting to additional chemical cost. One example is for *Plating 4* bath. Initial bath life was defined for (D x 2) months. When tall post technologies ramped in 2018, plate coplanarity defects and uneven metals were observed at earlier months with no assignable issue. Bath life was reduced to D months as part of corrective action increasing maintenance cost by 150%.

1.2 The Culprit

Controlling build-up of organic materials in different chemistries and process has been a constant challenge in semiconductor industry. J. Bahena, 2022 and J. Daviot, 2018 marked organic leaching as main source of efficiency degradation and severe product yield loss from ageing stripping bath in wafer and units scale.



Figure 3: Optical images of coupon surfaces post bath age studies displays representative images for A) 0-7 days and B) 7-15 day tests. C) Contact angle measurements results.^[1]

The presence of large organic molecules impedes the mobility of ions or any active chemical agent in chemistry. It lowers down the overall reactivity by adsorbing the Bond dissociation enthalpies (BDE) of nearby atoms or molecules. Aside from change in chemical property, physical property such as color, pH, specific gravity also signifies presence of organic material saturation.

Current indirect method of defining bath life is through monitoring of significant change in physical properties of different chemistries. *Figure 4* shows changes of solution color and pH signifying photoresist (organic) build-up overtime.



Stripping chemistry color, pH and viscosity changes over time Laboratory scale analysis and in-line analyzer in chemistry physical characterization has been established as part of new chemistry analysis frontier since 2010. What is left to be explored are accurate detection and quantification of organic

material build-up up for unique semiconductor chemistries correlating to efficiency in a given bath life.

1.2 Total Organic Carbon (TOC) Analysis

TOC is a well-known method in Wet industry that quantifies the amounts of organics directly from a sample. TOC analyzers convert organic carbon into Carbon dioxide (CO₂) and water (H₂O) by means of high temperature catalytic combustion or chemical oxidation.

TOC is usually paired with conductivity sensors which detects oxidized organic carbon traces. The difference between conductivity values of before and after oxidation is use to quantify organic carbon in sample.

Table 2: Comparison of known Organic compound analyzers

Method	Mechanism	Pros	Cons
High Temperature Combustion	Mix sample under oxidation catalyst under heated chamber	Rapid, efficient and compatible to wide range of organics	Metal salts and acid quickly damages combustion tube
Non-Dispersive Infrared Spectroscopy	Organic compounds absorb infrared radiation at specific wavelengths	Non- destructive	Sensitivity to interference from other gases or compounds
Nuclear Magnetic Resonance (NMR)	Provides molecular count absorption of through electromagnetic radiation	Characterizes chemical structure	Expensive and indirect concentration determination
High Performance Liquid Chromatography	Separate, identify and quantify each component in the sample	High sensitivity with high speed	Sample easily clogs on column, tedious sample preparation
Total Organic Carbon Analysis (TOC)	Directly analyze amount of organic carbon in sample	High speed analysis	Limitation to Low conductive chemicals

Table 2 highlights advantages and disadvantages of TOC compared to other known analyzers in industry from which TOC is only applicable to samples with conductivity measurement below 1000 mS/cm² usually applicable for ground water analysis (150 mS/cm²) Implementing TOC for semiconductor chemistry is a big challenge knowing that most chemistry are electrolytic, polar and highly conductive.

Multiple academic studies make use of advanced analytical tools to back-up and revamp TOC analyzers in wider range of industry applications including Nuclear Magnetic Resonance (NMR) or Furrier transform Infrared Spectroscopy (FTIR) but these methods are not favored in terms of manufacturing cost and limit of quantification.

1.2.1 UV Oxidation

The first use of UV in oxidizing organic material was introduced by Brownrigg in 1757. Since then, UV has been used to change both physical and chemical property of organic materials and is widely use in polymer industry. Some of its applications are also use in Wafer fab and bump during photolithography where property of photochemically amplified resist changed as the organic material is exposed to UV light making it soluble to a compatible solvent of almost similar polarity.

Equation 1:

 $R - C - O - H_{(organic)} + UV \rightarrow CO_{2(g)} + H_2O_{(l)} + R_{salt}$ Another application of UV is through material combustion. One common structure of organic materials is presence of conjugated Carbon (sp³, sp², sp). The covalent bonds between carbon and hydrogen in hydrocarbon structure (C-H) and the localized oxygen bond in carboxylic structures (C-O) when exposed in continuous UV is converted to Carbon dioxide, water and salt as by-product as shown in *equation 1*. At equilibrium, the amount of CO₂ corresponds to amount of organic carbon at start. The challenge comes with defining oxidation value of organic carbon through spectrometer absorbance peak and stability of CO₂ detection which is dependent to chemistry nature and properties

This paper makes use of chemistry profiling with Gaussian mixture modeling to softly predict and categorize multiple semiconductor chemistry nature, properties and reactivity.

1.2.1.a Gaussian Mixture Model (Unsupervised Learning)

Gaussian mixture model is a machine learning method used to determine the probability of each data point belongs to a given cluster (k). This study makes use of 3 component-Gaussian mixtures to categorized semiconductor chemistries *organics* as shown in *Figure 5*



Figure 5:

Gaussian model made of 3 clusters (k) on defined distribution (\sigma) and mean probability (\pi)

The mixing coefficients are probabilities *per se* and must meet $\sum_{k=1}^{K} \pi k = 1$ condition to optimally categorize chemistry class and isolate oxidized *organics* forms.

1.2.2 Carbonic acid

Carbonic acid is a compound which has a chemical formula of H_2CO_3 . This is formed from organic compounds that are reacted or exposed to any oxidizing agents or materials such as UV light, resulting to Carbon-Hydrogen bond of a compound being replaced by Carbon-X bonds where X = any electronegative element such as Oxygen and rapidly becomes CO_2 in H_2O due to its instability under ambient conditions. This compound is also considered as weak dibasic due to that it contains very low H^+ concentration compared to undissociated

Equation 2: (1st dissociation)

 $\begin{aligned} H_2CO_{3(aq)} + H_2O_{(l)} \leftrightarrow HCO_{3(aq)} + H_3O_{(aq)} \\ Equation \ 3: (2^{nd} \text{ dissociation}) \end{aligned}$





Huge Organic molecule forming carbonic acid after UV exposure

 $\rm H_2CO_3$ as seen on below dissociation mechanism, which means it contains higher $\rm H^+$ level on its first dissociation compared to second dissociation. However, this compound still gives pK_a value of 6.35 which gives pH value of lower than of 7 and a conductivity delta measurement of 0.7 mS/cm to 1.3 uS/cm when mixed with pure water on standard condition. Having this, carbonic acid is a conductive compound, hence, detectable by conductive probes. The challenge remains on the speciation of carbonic acid ensuring all are fully oxidized prior detection.

1.2.2.a Markov Modelling (Stochastic Method)

Markov modeling is a probabilistic technique that predict the future behavior of variables based on the current state. Markov model has a discrete number of states (*q*) and the transitions (*t*) between states (*S*) are nondeterministic. For example: there is a probability of transiting from a state q_i to another state $q_i : P(St = q_i | St-1 = q_i)$.

This study makes use of Markov chains and modelling to predict dissociation value of *organics* as it undergoes multiple oxidation steps (*Figure 7*). The probabilities of occurrence of each state and matrix of transition probabilities was used for *organics* speciation- characterizing good (chemistry baseline additives) from bad (contaminants) *organics* component being detected by the analyzer.



Figure 7:

Organics molecule speciation probability thru Markov's modelling showing oxidation factor predictability of organics

Citing the nature and mechanism of Carbonic acid formation thru UV oxidation of organic carbon and molecular characterization and isolation of *organics* from its original state, this study unveils the feasibility of TOC analysis for variety of semiconductor chemistry through carbonic acid tracing using in-house UV source and conductivity probes powered by multiple machine learning tools- A first to Industry contribution for zero chemistry maintenance.

2. 0 REVIEW OF RELATED WORK

Machine learning and artificial intelligence are increasingly gaining in prominence through data analysis and automation. Machine learning is also making profound changes in chemistry applications.^[2]

In the study of Glielmo, 2021, the use of Ensembles of Decision Tree (EoDT) to analyze the increasingly large amounts of chemical structural data to create an accurate and powerful atomistic and molecular simulations and model. This has resulted to present state-of-the-art algorithms for dimensionality reduction, density estimation, and clustering, and kinetic models used to analyze molecular simulation data as seen in *Figure 8*. Similar approach was used in this study breaking down huge undetectable, unclassified *organics* structure into smaller, classified and detectable form utilizing Gaussian and Markov's unsupervised learning and models.



Figure 8:

Illustration of the chemistry speciation steps to analyze data from molecular simulation and machine learning [3]

3.0 METHODOLOGY

2.1 Materials

The study covers the following Texas Instruments Chemistry listed in Section 1.1 *Model X* UV-Vis was used as UV source with wavelength ranging from 190 to 900 nm and *Model Y* conductivity probe with Multiple Electrode Cell was used to measure the sample conductivity response. Other metrologies such as HPLC, FTIR Spectrometer and NMR Spectrometers for confirmatory of Organic material tracing sourced out both internal and third-party institution. Lastly, SPC (Statistical Process Control) was also use to fact check tool real performance vs. prediction models.

2.2 Procedure

This study initially carried out by calibrating conductivity probe *Model Y* to measure initial conductivity value of Texas instruments chemistries. Probe was calibrated using reference standards from supplier to ensure accuracy. Conductivity value was reviewed with supplier to assess initial TOC capabilities. Use of cationic resin to reduce initial conductivity values for samples with readings exceeding probe limit of detection. Carbonic acid standards were use as sample controls to define method capability via conductivity measurements.

Aliquot of Samples were subjected for UV source after achieving ideal initial conductivity values, UV-Vis spectrometer was used to gather baseline absorbance peaks for each aliquot of base make-up (zero *organics*). Standard addition method was done for all samples where samples were spiked with known carbonic acid concentration and subject for UV source to characterize absorbance peak as shown in *Table 3*. Data were stored in analyzer database as reference value of each sample concentration and was use for chemistry profiling and speciation via machine learning. Post-conductivity measurements were also done to measure differences before and after UV oxidation.

Sample	Treatment	Differential Conductivity	Absorbance	Analyzer (3 rd party)
Blank	0	Yes		Yes
Standard	5	Yes	Yes	Yes
(Carbonic acid)	50	Yes	Yes	-
aciu)	100	Yes	Yes	
Sample	Young	Yes	Yes	Yes
	Mid-age	Yes	Yes	Yes
	Ageing	Yes	Yes	Yes
Sample +	Young	Yes		
Standard	Mid-age	Yes		
	Ageing	Yes		-

Table 3: Summary of sample treatments and analysis

Actual samples of varying life (young, mid-age, ageing) were used to measure absorbance peak and correlate carbonic acid concentration value through similar standard addition method. From there, Beer lambert's equation was used to quantify concentration with conductivity shift at defined absorbance. All samples including reference standards were subjected for third-party confirmatory test (HPLC, NMR, FTIR) to measure capability of new method developed.



Unsupervised Machine Learning framework of the study - Ensemble

Data stored during sample preparation and initial runs were used to categorized chemistry from sample type and *organics* type as seen in *Table 4*. Analyzer was taught to follow the decision or response depending on the result of chemistry profiling prior actual *organics* values measurements. The results of combined models and decisions were analyzed via EoDT as shown in *Figure 9* where the true value of *organics* read by the analyzer will decide required maintenance (bleedto dump or feed- to add) Actual tool response was monitored after establishing and standardizing new chemistry maintenance controls in *organics* concentration thru in-line analyzer powered by machine learning.

Tuble 1. Summary of Onsupervised maenine learning used						
Gaussian (Sample type)	Physical Property	Reactivity	Chemical Property	Decision		
Category	(√/≍)	(√/≍)	(√/≍)	?		
Markov (Organic type)	No Oxidation	Partial Oxidation	Full Oxidation	Decision		
Speciation	х	у	Z	?		
Analyzer (True Organics value)						
EoDT (Maintenance)	NONE	BLEED	FEED	?		

Table 4: Summary of Unsupervised machine learning used

4.0 RESULTS AND DISCUSSION

3.1 Conductivity measurement

Based on conductivity measurements of carbonic acid standards solution, all values remain constant throughout the experiment. This is relevant to ensure that target analyte in the solution matrix is masked and isolated during UV oxidation.

PROCESS	CHEMISTRY	VALUE (<1k ms/cm ²)	RESULT	TREATME NT
Standard	Merck	150	Good	
FAB &	Plating 1	>400K	Too High	<400
BUMP	Plating 2	>70K	Too High	<500
	Plating 3	>90K	Too High	<700
	Plating 4	>200K	Too High	<800
	Stripping 1	<300	Good	
	Stripping 2	<200	Good	
	Flux 1	<200	Good	
ASSEMBL	Deflash	<300	Good	
Y	Rewash	<400	Good	
	Etch	>4K	Too High	<500
	Plating 5	>10K	Too High	<500

Table 5: Conductivity assessment of standards and sample

As shown in *Table 5*, 46% of total baseline samples (time zero bath) analyzed shows low initial conductivity value (<1000 ms/cm²). Most of these samples are made of polar aprotic solvents hence uncontrolled conductivity is no issue. Remaining samples on the other hand showed significantly high conductivity value exceeding limit of detection of conductivity meter and calibration curve. All of these samples are electroplating solutions of Bump and assembly where presence of free-ions is what causing high conductivity value.

Conductivity value greatly improved after cationic resin treatments. Initial runs encountered crystallization during room temperature treatments specifically for *Plating 2*.

This is due to presence of boric acid component crystallizing below 40 °C. Issue was addressed by using a hot plate to mimic operating temperature and same treatment was use for chemistry processing at elevated temperature.

3.2 UV Oxidation

UV spectrometer results showed distinct broad peaks for standard carbonic acid standards from which absorbance slope is at 0.9998. This indicates good characterization of oxidized organic carbon upon exposure to UV. A full broad peak indicates full spectrum indication while a half plot indicates partiality.

TI chemistry at time zero showed characteristic absorbance peaks except for *Plating 5* and *Flux 1* chemistry. These were addressed by changing sample preparation of both samples. For *Plating 5*, Millipore filtration was conducted prior UV analysis. This is to eliminate excess foaming which affects the light absorption under spectrum evident on spectrum noises. For *Flux 1* sample, acid digestion was made to purify the sample. Based on the spectrum, analyte is nowhere to be found indicating concentration is too small to detect.



Figure 10:

Machine Learning- Spectrum of Flux wash chemistry before (A) and after (B) sample digestion; Spectrum of Tin matte plate before (C) and after (D) filtration to enable distinct peak detection during UV absorbance

Standard addition method shows good plot and r^2 for each sample treatments. Absorbance value of varying bath life also showed strong linear correlation to almost all samples expect for *Stripping 1* and *Plating 5* chemistry. It was confirmed through HPLC that both chemistries tend to produce amphoteric by-products at ageing condition which masked the detection of oxidized organic carbon in any spectrophotometer. This was isolated by adding an anti-mask agent which recovered peak value by 85%.

Based on the result of Gaussian modeling, chemistry profiled in terms of physical property, chemical property and reactivity was categorized into 4 Class and 8 functional groups. Data was used to profile new chemistry coming from same nature. For example, *Plating 3* tested positive to Tollen's test (reactivity) denoting that organic is high in molecule (chemical property), neutral (physical property) and made of Aldehyde detected at 270 nm. All chemistry with similar nature was treated under Class E- aldehyde.

CLASS A		CLASS B		
Carboxy, acid	Amine	Carboxy, neutral	Amide	
Plating 2	Stripping 1	Deflash &	Plating 1	
(210 nm)	(200 nm)	Rewash (300 nm)	(210 nm)	
CLASS S		CLASS E		
Alkene	Alcohol	Aldehyde	Ketone	
Plating 4	Stripping 2 &	Plating 3	Plating 5	
(290 nm)	Flux 1 (300 nm)	(270 nm)	(280 nm)	

3.3 Carbonic acid as New Chemistry Controls

The absorbance measured for each standard, baseline sample (time zero), standard addition and varying age bath was used to isolate and correlate detected oxidized organic carbon in the form of carbonic acid- a by-product of Carbon + UV.

Shifts in conductivity value was also observed for ageing samples exposed to UV-Vis oxidation. The difference in the conductivity before and after sample treatments plus the difference in absorbance peak used in standard addition method is at 98.33% matched with theoretical Beer-lambert's value. This indicate that the developed method of analyzing carbonic acid trace through UV spectrometer and Conductivity meter can be a benchmark in quantifying amount of organic carbon present in TI Chemistries.

Sample	mS/cm ²	Abs at	mS/cm ²	Beer-	%
(Plating 4)	Initial	290nm	Final	lambert's	Matching
Blank	150	0.00	150	0	-
5	<400	0.01	<400	0	-
50	<500	0.00	<500	0	-
100	<700	0.01	<700	0	-
Actual Samples (Markov model reference)					
Time -0	<710	0.8	>710	15	98.33%
Mid age	<720	1.2	>720	10	100.8%
Ageing	<850	1.6	>850	7.5	100.0%
π_{i}		0.4	Markov's Coefficient		

Table 7: Conductivity measurements of standards and sample analysis using Markov's model

Using *Plating 4* actual samples data, the transition probability of ageing bath in response to concentration value (absorbance peak) is at $\pi_i = 0.4$ showing strong predictability for quantifiable oxidized *organics* at optimum defined absorbance of 290 nm denoting full oxidation of unwanted *organics* defined during UV-profiling.

3.4 New Method Confidence

NMR results showed comparable carbon concentration slope and r^2 compared to new method as seen on *Figure 11*.

In terms of concentration, the actual NMR c-count is relatively higher which can be attributed to possible presence of inorganic carbon detected during chemical analysis. The result of external laboratory analysis strengthened the correlation of carbonic acid (oxidized organic carbon) concentration to chemistry life.



Figure 11:

A) r² comparison of NMR to HPLC-0.9999; B. r² comparison of NMR to New Analyzer-0.9998

3.5 New Chemistry Maintenance Solution

New Chemistry limit and maintenance was defined by EoDT from combined data of:

- a. Gaussian's model during UV-profiling
- b. Markov's model during Carbonic acid measurements

c. SPC trend of bath life vs. Yield, Inspection

Based on the results shown at *Table 8*, almost all chemistry is low risk in enabling zero chemistry maintenance starting with chemistry life extension except for deflash chemistry which showed inconsistent SPC yield degradation (-50%) at lower organic carbon concentration hence recommended to tighten bath life. Additional tool to sample chemistry is recommended to further extrapolate data.

Table 8: Summary Results used for EoDT Frameworkresulting to Chemistry life extension & Zero maintenance

C C	<i>,</i>	~ ~			
	Chemistry	Gaussian	Markov	SPC	↑ Life
FAB	Plating 1	B2	0.30	Y	100%
& BUMP	Plating 2	A1	0.10	Y	300%
	Plating 3	E1	0.20	Y	300%
	Plating 4	S1	0.40	Y	130%
	Stripping 1	A2	0.10	Y	50%
	Stripping 2	S2	0.10	Y	150%
	Flux 1	S2	0.20	Y	166%
ASS'Y	Deflash	B1	1.20	Ν	-50%
	Rewash	B1	0.70	Y	266%
	Etch	-	0.40	Y	266%
	Plating 5	E2	0.10	Y	50%

New bath maintenance method was introduced by implementing partial dumping for chemistry with sudden spike of organic carbon build up instead of complete dumping once original life limit was reached. As part of continues improvement towards lights-out manufacturing, the developed analyzer was converted to in-line tool to monitor organic carbon build-up real time. Made of UV Lamp and conductivity probes, the new analyzer re-defines total organic carbon analysis capabilities for complex chemistries of semiconductor manufacturing applications.



Figure 12:

a) Analyzer exterior, b) Interior showing sample inlet, Sensors A & C, UV chamber B, Processor D and Signal Converter E, then Outlet, c) Multiple tools linked to in-line analyzer

Scheme: [1] Sample is injected to tool. [2] UV-source oxidized sample in defined wavelength and parameter converting *organics* to carbonic acid [3] 2 conductivity probes measure differential conductivity value measuring presence carbonic acid in real-time [4] Data stored for learning

5.0 CONCLUSION

First to industry universal chemical analyzer was developed to prove correlation of organic material build-up in multiple fab, bump and assembly's chemistries that limits life and degrades efficiency in semiconductor manufacturing. Concept was based in lab scale oxidation of total organic carbon into carbonic acid thru a UV-source isolated and characterized via Gaussian and Markov's modelling for the detection of oxidized specie thru conductivity measurements. Multiple challenge surrounding out of tolerance conductivity measurements and spectrum noises were solved through cationic resin treatments and sample preparation modification. Method of standard addition method was also used to trace specie of carbonic acid originating from ageing bath. Novel method gained 99.989% success rate in tracing organic carbon in solutions compared to complex and highend analyzer in market. From strong correlation of organic concentration to yield degradation, method of defining new chemistry life was standardized to TOC (Total organic carbon) concentration measurements. With new control, existing chemistry life can be extended up to 150 to 300% except for deflash chemistry which requires 50% cut in current bath life due to abnormal spike in carbon ppm requiring further study. New method of bath maintenance and reaction plan was defined from complete bath change to partial bleed and feed only controlling concentration values prognosed by multiple learning ensembles (EoDT). The new maintenance system was controlled by Novel analyzer that detects build-up of organic carbon concentration in real-time. As overall cost impact, the new system improved chemistry cost per pattern and cost per pin by 18%. New in-line life monitoring and auto-maintenance eliminated 15% Nonvalue-added activity for Engineers supporting tool bath maintenance and 10% tool availability improvement from zero scheduled down time.

The development of the new analyzer powered by machine learning opens a new milestone in chemistry applications. To achieve its ultimate universal applications, continues testing to wider variance of chemistry samples and datasets are recommended to further train neural networks for more complex and advance algorithms.

6.0 RECOMMENDATIONS

New analyzer is for universal chemistry use and is online to more than 15 chemistry and 30 chemical suppliers. Any new chemistry especially of high conductivity value need to undergo similar assessment prior installation of in-line analyzer. Sample must obtain a unique characteristic peak and conductivity value that is within the current tolerance. Else, challenges need to be resolved through sample preparation, method adjustments or new ensemble learning. Current analyzer dimension is 0.2 m X 0.3 m to set-up as inline monitoring. Currently sourcing out to make a compact, smaller and portable versions. It is recommended for new analyzer to equip a built-in cryostat for chemistry with processing at elevated temperature else must have a short chemical line from tank source to minimize any heat loss and ensure measurement accuracy.

It is also recommended to replicate analysis results to all production tools to gather more data points to further widen the process margin of extended bath life and monitor any response shifts in EoDT framework due to wider datasets. The new controls in defining bath life through organic concentration and Automatic bleed and feed system is recommended to all processes and chemistries with suspected organic material build-up resulting to manufacturing challenges and early chemistry failure.

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9.0 ABOUT THE AUTHORS



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10.0 APPENDIX N/A