Fuzzy tree classification system for fault diagnosis on Ion implanter

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Abstract. Ion implanter is critical to modern integrated-circuit (IC) manufacturing. Ion implanter requires a long process due to low acceleration and high concentration process, which results in low productivity and becomes a bottleneck in the semiconductor fabrication. Furthermore, the wafer is not re-workable if existing error operation either caused by the operator or the machine. Therefore, it is important to develop a real-time fault detection system to minimize the probable down time of the ion implanter. In this work, a real-time fault detection system, which is based on the Fuzzy Tree Classification Systems (FTCS), is proposed to monitor the operation of the Eaton NV6200A/AV ion implanter. Two datasets, the 26-recipe and the 42-recipe cases, provided by a renowned wafer foundry in Taiwan were used to test the performance of the proposed FTCS. The datasets were obtained through the SECS-II interface. Test results demonstrate that the proposed FTCS can work real-time for fault detection of the Eaton NV6200A/AV ion implanter.

1. Introduction
Ion implanter is critical to modern integrated-circuit (IC) manufacturing. An ion implanter [1]-[3] consists of an ion beam generator to generate an ion beam and steer ion into the substrate such that the ions come to rest below the surface. Ion implanters require a long process because of using low acceleration and high concentration process. Several wafers are rotated by the discs during the process, which may break thin wafers. Furthermore, the wafer is not re-workable if existing error operation either caused by the operator or the machine. Ion implanter results in low productivity and becomes a bottleneck in the semiconductor fabrication. Ion implanter has been changed from a complicated prototype to a computer controlled automated equipment. The designs of ion implanters are developed to meet the continuous operations at high production efficiencies under a minimal testing regime and an initial setup. However, ion implanters still have intrinsic potential hazards which can never be completely avoided from design. Ion implanters have five main categories of hazards, which are high voltage, hazardous materials, mechanical systems, ergonomic issues and radiation. These categories can interact with each other to raise hazards that may not be readily recognizable to personnel. Therefore, it is important to construct a real-time fault detection system to minimize the probable down time of the ion implanter. Although the supplier supports a digital scanning system to remind the operator for improper operations, other components such as the extraction electrode, filament source, mass analysis system, acceleration system, and arc chamber, are also required monitoring.
Well-trained operators can monitor the operation of ion implanter though the statistical process control (SPC) [4]-[5] for each component. However, there is no human-error free and automatic tool to real-time monitor the operation of ion implanter [6]-[7]. To overcome this drawback, a real-time fault detection system based on the Fuzzy Tree Classification Systems (FTCS) [8]-[10] is proposed to monitor the operation of ion implanter. The classification approaches based on the fuzzy set theory have been successfully applied to pattern recognition problems. The datasets of all recipes are collected from the Eaton NV6200A/AV ion implanter with a renowned wafer foundry in Taiwan. The Eaton NV6200A/AV with the Dual Cassette Loader / Unloader kit installed is shown in Figure 1, which is a medium current ion implanter. The Eaton NV6200A/AV can implant dopants at beam energies from 10 to 190 KEV. Common gases include Arsine, Helium, Boron Trifluoride, Argon, Carbon Dioxide and Phosphine are available for implantation. The Eaton NV6200A/AV is designed for implanting 6” wafers, but carrier wafers are available for 4” wafers or pieces.

![Figure 1. The Eaton NV6200A/AV with the dual cassette loader.](image)

The schematic of an ion implanter is displayed in Figure 2 [11]. Ion implanters should be maintained under high vacuum to admit linear free move of the ions without phenomenon of dispersion due to collisions with adjacent gas molecules. There are four components of the ion implanter, which are ion source, extractor, mass analysis slit, and accelerator. At first, the ion beam is created by the extraction from the ion source using electromagnetic fields. Next, ions are directed into a mass analysis slit in which the beam is focused and bent through a right angle. A combination of the mass to charge ratio of the ions and electromagnetic field characteristics determines the radius of the bend. Mass analysis slit selects ions with a particular mass to departure the mass analysis slit by an electromagnetic lens. Accordingly, only the required dopant atom coming from the ion source is chosen from different ions. Finally, the selected beam of ions is accelerated by an accelerator with high energies, which are ranging from sub-keV to MeV values. The ion beam with high energy is moved by electromagnetic fields, then it impacts on the semiconductor surface.
Currently, several tens to hundreds of recipes in wafer fabrication are used in a typical semiconductor foundry one day. Recipes are sets of instructions for a process type on a tool in semiconductor manufacturing or describing how the equipment should process its material [12]. The recipe of the process should be qualified to cause a tool to carry out a process. In this way, a recipe can be regarded as a class. Therefore, the fault detection of ion implantation becomes a classification problem with a large number of classes.

The measured signals in digital scanning system provided by the supplier contain beam current, filament current, magnetic field strength, filament voltage, discharge voltage, etc. Although various signals can be collected, not all measured signals are useful in classification. According to the product design process, the design knowledge domain contains the following ten attributes: beam-line pressure, beam current, acceleration/deceleration voltage, chamber pressure, extraction electrode current, extraction electrode voltage, filament current, filament voltage, high voltage power supply current, and magnetic field strength. The above 10 attributes involve the 4 components of the ion implanter. Two datasets, the 26-recipe and the 42-recipe cases, provided by a renowned wafer foundry in Taiwan were used to test the performance of the proposed FTCS. Each recipe comprises 1,100 to 12,000 wafers.

Organization of the rest of the paper is as follows. Section II illustrates the proposed Fuzzy Tree Classification Systems. Test results obtained by the proposed he Fuzzy Tree Classification Systems on an Eaton NV6200 ion implanter are given in Section III. Finally, Section IV makes a conclusion.

2. Methodology

2.1. Fault detection and identification

Although the statistical process control (SPC) procedures and quality tools can help a well-trained engineer to monitor process behaviour and find solutions for production issues. However, there is no automatic and effective tool to monitor all the components simultaneously and consider interactions between each component. Figure 3 describes the key idea of the proposed fault detection and identification scheme. There are two major parts in our approach. The first part is the fault detection. We treat a collected data pattern of the wafers associated with a recipe as a class. Then, the FTCS is developed to classify the class of the data pattern of the working wafer. The data patterns are obtained using SEMI Equipment Communications Standard Part 2 (SECS-II) [13]-[14] designed by Industrial Technology Research Institute (ITRI) in Taiwan. Figure 4 shows the SECS-I protocol and SECS-II messaging between host and equipment. The SECS-II defines the interpretation of messages exchanged between a host and an equipment. The messages are divided into various categories of activities which contain specific messages. For example, a request for information and the corresponding data transmission is such an activity.
If the classified data pattern is consistent with its destined recipe, we conclude that the ion implanter works well; otherwise, we will inform the operator to check with the recipe command of the working wafer. If it is correct for the command, we will proceed with the second part of our approach. The second part is the fault identification, which is used to identify the faulty attribute. When the number of detected faults exceeds the statistical classification error rate of the FTCS, the equipment engineer will be informed to check with the component which corresponds to the faulty attributes.

**Figure 3.** A fault detect and identification scheme for ion implanter.

The FTCS proposed in this paper is an efficient and effective classification tool, which overcomes the drawback raised in the conventional fuzzy rule-based classification system [15]-[16] in the aspects of...
computational complexity due to the vast number of attributes and fuzzy subsets. The major factor that adds to the efficiency and effectiveness of FTCS is the fuzzy cluster tree. The fuzzy cluster tree allows the fuzzy partition for classes to be finer, and thus the training time can be shorter while the classification rate can be higher.

The fault identifier proposed in this paper is a by-product of the FTCS. It allows us to easily identify the faulty attributes that occurred on the branch of FTCS, which is a leaf of the FTCS.

2.2. Fuzzy tree classification systems

Basically, the framework of the FTCS comprises two steps: the fuzzy rules generation and the classification of data pattern. In the first step, the training procedure generates the fuzzy rules according to a set of data patterns with given classes. In the second step, a fuzzy reasoning scheme is utilized to classify an unknown data pattern though the fuzzy rules. The fuzzy rules generation and the classification procedure are described as below.

**Fuzzy rules generation:** Denote the $g$ data patterns of $n$ attributes $x_p = (x_{p1}, \ldots, x_{pn})$, $p = 1, \ldots, g$, as the training data set. $C_1, \ldots, C_M$ denote as the $M$ classes. The fuzzy if-then rules of the FTCS are defined as the following type.

If $x_{pi}$ is $A^k_{i1}$, ..., $x_{pi}$ is $A^k_{it}$, then $x_p$ belongs to $C^k_{i1} \times \ldots \times C^k_{it}$ with $CF = CF^k_{i1} \times \ldots \times CF^k_{it}$, $i_1 = 1, \ldots, K$ and $i_t = 1, \ldots, K$, where $K$ denotes the number of fuzzy subsets on each axis of the pattern space, $A^k_{i1}, \ldots, A^k_{it}$ are partitioned fuzzy intervals in each axis, $C^k_{i1} \times \ldots \times C^k_{it}$ denotes the consequent, i.e. one of the $M$ classes, and $CF^k_{i1} \times \ldots \times CF^k_{it}$ denotes the grade of certainty of the fuzzy rule. $C^k_{i1} \times \ldots \times C^k_{it}$ is determined by the maximal class compatibility $\beta_c$ with the partitioned region $A^k_{i1} \times \ldots \times A^k_{it}$. $CF^k_{i1} \times \ldots \times CF^k_{it}$ is calculated by the difference between $\beta_c$ and the average of class compatibility for rest classes. Both $\beta_c$ and $CF^k_{i1} \times \ldots \times CF^k_{it}$ are computed using the training data set.

**Classification of data pattern:** Denote the unknown data pattern be $x_p' = (x_{p1'}, \ldots, x_{pn'})$. The weighted grade of certainty of $x_p'$ with class $CF^k_{i1} \times \ldots \times CF^k_{it}$ is defined as the multiplication of the grade of compatibility of $x_p$ with the partitioned region $A^k_{i1} \times \ldots \times A^k_{it}$ and the $CF^k_{i1} \times \ldots \times CF^k_{it}$. The class which corresponds to $CF^k_{i1} \times \ldots \times CF^k_{it}$ has a maximal weighted grade of certainty of $x_p'$ is the resulted class of $x_p'$.

3. Test results

There are several tens to hundreds of recipes for wafer fabrication in a typical semiconductor foundry one day. A recipe can be regarded as a class. Generally, various attributes are measured from the ion implanter. However, some attributes are not helpful in classification. The following 10 attributes are recommended: beam line pressure, chamber pressure, filament current, filament voltage, beam current, high voltage power supply current, magnetic field strength, extraction electrode voltage, extraction electrode current, and acceleration/deceleration voltage. The above 10 attributes involve the four components of an ion implanter. Table 1 lists the units and corresponding components of the above 10 attributes. Two datasets, the 26-recipe and the 42-recipe cases, provided by a renowned wafer foundry in Taiwan were used to test the performance of the proposed FTCS. The data pattern was obtained through the SECS-II interface. Each recipe comprises a 1,100 to 12,000 wafers.
Table 1. The components and units of the 10 attributes.

| Attribute                     | Unit   | Component       |
|-------------------------------|--------|-----------------|
| Chamber pressure              | Torr/e6| accelerator     |
| Beam line pressure            |        |                 |
| Filament current              | Amps   | ion source      |
| Filament voltage              | Volts  |                 |
| Beam current                  | mA     | mass analysis   |
| High voltage power supply     | µA     |                 |
| Magnetic field strength       | KGAuss |                 |
| Extraction electrode voltage  | Volts  | extractor       |
| Extraction electrode current  | mA     |                 |
| Acceleration/deceleration     | KV     |                 |

We randomly divide the data patterns into ten parts. Nine parts are used as training data set and one part is used as test data set. The value of fuzzy partitioned intervals is \( k = 12 \) and a triangle nonnegative membership function is utilized. Circulating the training data set and test data set for ten times, Table 2 and Table 3 show the classification error rate (%) using ten-fold cross validation of the 26-recipe case and the 42-recipe case, respectively. The classification error rate is defined as the percentage of misclassified classes out of the total classes in the validation data. The classification error rates are mostly under 3% and no more than 3 out of 26 or 42 are over 3% but still within 6%. All the faulty attributes are also identified. Above all, it takes only 0.08 seconds in an Intel Corei7 PC to classify a data pattern. Test results reveal that the proposed FTCS can work real-time for fault detection of ion implanter.

Table 2. The classification error rate (%) of the 26-recipe case.

| Index | Error | Index | Error | Index | Error |
|-------|-------|-------|-------|-------|-------|
| 1     | 0     | 10    | 1.17  | 19    | 2.7   |
| 2     | 2.55  | 11    | 0.84  | 20    | 1.77  |
| 3     | 0.08  | 12    | 0.95  | 21    | 2.3   |
| 4     | 0     | 13    | 0.1   | 22    | 0.06  |
| 5     | 0     | 14    | 0.78  | 23    | 0     |
| 6     | 2.52  | 15    | 0.42  | 24    | 0.57  |
| 7     | 2.29  | 16    | 0.4   | 25    | 0     |
| 8     | 1.36  | 17    | 0     | 26    | 0.47  |
| 9     | 2.05  | 18    | 0     |       |       |
Table 3. The classification error rate (%) of the 42-recipe case.

| Index | Error | Index | Error | Index | Error |
|-------|-------|-------|-------|-------|-------|
| 1     | 0     | 15    | 0.45  | 29    | 0.08  |
| 2     | 2.69  | 16    | 0.48  | 30    | 0.32  |
| 3     | 0.08  | 17    | 0     | 31    | 0.45  |
| 4     | 0     | 18    | 0.58  | 32    | 0     |
| 5     | 0.26  | 19    | 4.2   | 33    | 0     |
| 6     | 1.95  | 20    | 3.46  | 34    | 0     |
| 7     | 4.15  | 21    | 2.55  | 35    | 0.16  |
| 8     | 5.52  | 22    | 0.06  | 36    | 0     |
| 9     | 3.21  | 23    | 0     | 37    | 3.08  |
| 10    | 3.18  | 24    | 0.37  | 38    | 0     |
| 11    | 0.82  | 25    | 0     | 39    | 5.93  |
| 12    | 1.31  | 26    | 0.37  | 40    | 1.26  |
| 13    | 0.1   | 27    | 0.32  | 41    | 0.1   |
| 14    | 0.74  | 28    | 2.91  | 42    | 0.21  |

4. Conclusion
The contribution of this paper has three folds: (i) proposing a real-time fault detection for the ion implanter, (ii) proposing an efficient and effective classification tool, FTCS, and (iii) proposing a FTCS based faulty attribute identifier. The benefits of FTCS based faulty attribute identifier are its simple structure and effective partition of fuzzy subsets. Two datasets, the 26-recipe and the 42-recipe cases, provided by a renowned wafer foundry in Taiwan were used to test the performance of the proposed FTCS. The classification error rates are mostly under 3% and no more than 3 out of 26 or 42 are over 3% but still within 6%. Test results reveal that the proposed FTCS can work real-time for fault detection of ion implanter. Some practice engineering systems probably suffer a complicated fault detection problem. Future researches will focus on the extension of the proposed FTCS to resolve complicated fault detection problems.

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References
[1] Yamada K and Kashiwagi H 2020 Low-charge-state ion production by a laser ion source for the TIARA ion implanter Review of Scientific Instruments 91(1) 013305
[2] Li H, Wang Z S, Zhang S J, Pelenovich V O, Ren F, Fu D J, Liu C S and Ai Z W 2016 Study of doping uniformity of a 200 kV ion implanter by RBS and sheet resistance measurements Nuclear Science and Techniques 27(3) 55
[3] Suresh K, Balaji S, Saravanan K, Navas J, David C and Panigrahi B K 2018 Development of a simple, low cost, indirect ion beam fluence measurement system for ion implanters, accelerators Journal of Instrumentation 13 P02033
[4] Berlemann M, Freese J and Knoth S 2020 Dating the start of the US house price bubble: an application of statistical process control Empirical Economics 58(5) pp 2287-2307
[5] Hernandez M and Novoa F 2020 Evaluating variability of automatic process control of the moisture control in medium density fibreboard line, using statistical process control *IEEE Latin America Transactions* 18(5) pp 833-837

[6] Yang S Y, Sun X H, Ma M Y, Zhang X and Chang L H 2020 Fault detection and identification scheme for dual-inverter fed OEWIM drive *IEEE Transactions on Industrial Electronics* 67(7) pp 6112-6123

[7] Plakias S and Boutalis Y S 2020 Fault detection and identification of rolling element bearings with Attentive Dense CNN *Neurocomputing* pp 208-217

[8] Rabcan J, Levasenko V, Zaitseva E, Kvassay M and Subbotin S 2019 Application of fuzzy decision tree for signal classification *IEEE Transactions on Industrial Informatics* 15(10) pp 5425-5434

[9] Remya S and Sasikala R 2019 Classification of rubberized coir fibres using deep learning-based neural fuzzy decision tree approach *Soft Computing* 23(18) pp 8471-8485

[10] Teekaraman D, Sendhilkumar S and Mahalakshmi G S 2020 Semantic provenance based trustworthy users classification on book-based social network using fuzzy decision tree *International Journal of Uncertainty Fuzziness and Knowledge-Based Systems* 28(1) pp 47-77

[11] Salvendy G 2007 *Handbook of Industrial Engineering: Technology and Operations Management*, 3rd ed., New York: John Wiley & Sons

[12] Lars M, John W F and Scott J M 2014 *Production Planning and Control for Semiconductor Wafer Fabrication Facilities: Modeling, Analysis, and Systems*, New York: Springer-Verlag

[13] Cheng F T and Lin M T 2001 Enhancement of semiconductor equipment communications using a web-enabled equipment driver *IEEE Transactions on Semiconductor Manufacturing* 14(4) pp 372-380

[14] Zurawski R 2015 *Industrial Communication Technology Handbook*, 2nd ed., CRC Press, Boca Raton

[15] Mamaghani A S and Pedrycz W 2020 Structural optimization of fuzzy rule-based models: Towards efficient complexity management *Expert Systems with Applications* 152 113362

[16] Cerqueira T L, Bertoni F C and Pires M C 2020 Instance genetic selection for fuzzy rule-based systems optimization to opinion classification *IEEE Latin America Transactions* 18(7) pp 1215-1221