TLP Seminar Abstract Cover Page

**1. Seminar:** Singapore Assembly & Test Seminar (SATS)

**2. Paper Title:** BURN Termination Disposition System Development using Unsupervised/Supervised Natural Language Processing

**3. “Elevator Pitch”: What is the Main Point? [**required for **Systems Solutions Technical Seminar**; **optional** for all other TLP seminars**].**

* The development of a standalone system that integrates machine learning techniques to categorize the oven termination events and provide first-pass resolution to Engineering Data Technicians (EDT) when encountering termination events.
* A web application is designed to automate the termination information query process, disposition provision, and communication email generation, significantly reducing the daily workload.
* Collaborative effort between Test Solution Engineering (TSE) and EDT. EDT uses this application extensively for Ambyx6 terminated production lots.

**4. Answer the following questions to describe how your paper will meet the review criteria:**

1. **Original / Innovative:** Contributes highly to state of the art. Features new, advanced, or original methods. Has not been published elsewhere (internally or externally) OR significantly develops or improves previously published work.

How does this work contribute highly to state of the art or feature new, advanced, or original methods?  
🡪 The method proposed in this paper is a new innovative idea that applies unsupervised/supervised machine learning algorithms to oven termination error messages to predict categories and propose solutions for those categories based on subject matter expert recommendations. Additionally, the system has been developed with a user-friendly web application.

* Has this been done before (external or internal)? 🡪 No, it has not been done before and this is a new idea.
* Has this paper previously been published elsewhere? If so, does it significantly expand on previously published work? (If this exact paper has been published in a different TLP Journal or Seminar, we will not accept it for this seminar.)🡪 No, this paper is not published previously.

1. **Impact / Significance:** This topic is relevant to Micron’s business. It solves a problem, reduces cost, enables new products, increases performance, establishes competitive edge, or otherwise has some positive impact on Micron's business.

* How does this abstract solve a problem, reduce cost, enable new products, increase performance, establish competitive edge, or otherwise have some positive impact on Micron's business?

🡪 This project aims to improve work efficiency (performance) between two related teams, TSE and EDT. Repeated and tedious work between teams can be avoided/reduced by applying the suggested method in this paper. The ability to automatically draft communication emails also helps align email formats and significantly reduces the workload on the EDT side because no manual work is required for most cases. The total number of termination cases per workweek can be up to 140 times, as shown in the figure below. The project will become more important once the number of termination cases increases.

Analyzing new error categories through the web application proposed in this paper is also possible. Since the new error message is a message that has not been trained in the existing model, we will continue to return the result value of ‘None.’ The accumulated ‘None’ cases will be classified as new cases through discussions between professional engineers and domain workers of related departments, and solutions to problems will be discussed. Therefore, the proposed method can also detect new types of errors, ultimately reducing the overall termination case.

A graph of a bar chart

Description automatically generated with medium confidence

1. **Technical Merit:** Contains sufficient technical depth and high-quality engineering work; shows specific results with explicit supporting data. Science is valid without logical fallacies. Work is complete, uses scientific methods, draws correct conclusions, and accurately analyzes the data.

* Explain how this work demonstrates technical depth and high-quality engineering per the definition above.

🡪 The novelty of this research can be stated as follows:

1. **Applying Natural Language Processing (NLP) technique to manufacturing equipment event logs:** In the semiconductor field, machine learning methodology is mainly used to analyze quantitative data. However, the method proposed in this paper is used to analyze event logs of semiconductor equipment, not quantitative data. Therefore, the NLP algorithm is directly applied to manufacturing equipment event logs to change the Natural Language format to Quantitative Vector format.
2. **Combination use of Unsupervised/Supervised Machine Learning Algorithms:** The proposed method in this paper applied both unsupervised and supervised ML algorithms. First, we applied an unsupervised clustering algorithm to cluster similar error message logs. Since it is difficult for engineers to label and check about 3000 raw error message logs individually, we first applied an unsupervised learning clustering algorithm to cluster roughly similar event logs.

After clustering, domain experts reviewed the clustering results to see whether similar errors belong to the same clustering group. They also labeled clustering results into types of errors. After labeling the data, we could apply a supervised classification algorithm to classify error messages.

1. **Building web applications for actual users:** We made web applications for actual users, applying the suggested methods in this paper. The purpose of building web applications is that users resolve real-time termination cases through easy access to the websites. Through the website, users simply key in ‘Lot Number’ and ‘Oven Number’ as the input. As an output of the application, the website shows the Disposition method that matches the types of errors.

Furthermore, we have continuously enhanced our web app based on valuable feedback from real users, making it even more practical and user-friendly. The application not only suggests dispositions but also facilitates users in querying the required information from various data sources, integrating all the information into a comprehensive solution.

1. **Collaboration:** Work demonstrates collaboration between teams or across geographical / functional boundaries

* Without naming co-authors, explain the extent to which you’re collaborating.

🡪 This project was successfully implemented due to excellent collaboration between many teams across products and sites, such as NAND TSE and mNAND TSE from Singapore and Penang sites. After using the system, the EDT team also provided their requirements and feedback for improving the system to the project team.

1. **Forward Looking:** Demonstrates practical application, a basis for future work, and viable path forward.

* What is the practical application for this work? What is the future work?

🡪 Currently, the application/system is commonly used on Ambyx6 products at the Singapore (MSB) site, which runs through NAND/mNAND BURN steps. The forward path will be to fan out this Machine-Learning system to the PENANG (MMS) site, and this goal is already underway with the collaboration of the MMS TSE team. In the future, the team will explore the feasibility of applying the system to other products (e.g., Ambyx5 and DRAM) or steps (e.g., CHAMBER).

1. **Insert your extended abstract on the next 1–2 pages.**

BURN Termination Disposition System Development using Supervised/Unsupervised Natural Language Processing

***Abstract:* When termination occurs at the Burn oven sessions, EDT technicians primarily check the error messages and resolve the termination. If the technician cannot handle the problem, the case will be escalated to TSE. After escalation, TSE investigates issues and gives resolution to EDT technicians through email. However, replies might be delayed when TSE cannot reply, such as on night shifts or non-working hours. As a result, it can cause work inefficiency for the related teams. Therefore, this paper aims to develop web applications using machine learning to improve work efficiency for related teams, especially in the absence of TSE. The overall methodology is collecting past data logs from the Burn oven session, applying the NLP technique and machine learning algorithms to train our model, and suggesting a disposition method through a web application. First, Perl script collects oven error message data, about 3000 data sets, and TF-IDF will be applied to error message data sets. Second, clustering algorithms are tested, and DBSCAN will be applied to error messages to cluster data. After that, the data is labeled through reviews by experienced engineers. Third, classification algorithms are tested, and SVC, which has the highest accuracy, is chosen for the web application. Last, the Web application is developed under the Flask environment. Web applications can handle up to 140 termination cases per week. Also, it can be used to crunch through oven error logs and look for the commonality of the termination error message. Ultimately, it will reduce the overall termination cases.**

***Index Terms:* Decision support systems, Machine learning, Semiconductor devices, Support vector machines**

# Introduction

A screen shot of a computer

Description automatically generatedEngineering Data Technicians (EDT) and Test Solutions Engineers (TSE) have different roles but work closely together to ensure smooth back-end production line testing. TSE members prepare and maintain test programs to test dies while the EDT team monitors and handles the manufacturing issues. Since ovens need to run 24 hours/7 days, real-life manufacturing issues are bound to arise. The EDT team will perform first-level troubleshooting of manufacturing issues on the production line. EDT will escalate issues to TSE whenever they encounter issues they cannot resolve. After escalating the issues, TSE will investigate and provide a resolution or debug process to the EDT team to handle the issue. However, when errors occur even during non-working hours (weekends, midnight, and holidays), TSE may not be available immediately to provide dispositions, causing delays. Delayed dispositions lead to termination lots occupying the oven for extended periods. This delay affects production cycle time due to increased test cycles, especially BURN steps with longer test times. This paper aims to improve the work efficiency of the BURN TSE and EDT engineers, especially in the absence of TSE. We will suggest a new methodology for solving the problems mentioned above by developing a web application that applies Machine Learning (ML) algorithms.

# Methodology

The overall methodology is collecting past data logs from the Burn oven session, applying the Natural Language Processing (NLP) technique, and using ML algorithms to train our model to classify termination messages into different classes. Classification results will be shown on the developed Web application. These results also help domain experts study the classified groups to permanently resolve the termination or provide instruction to EDT to resolve the issues on the spot.

The methodology can be divided mainly into four parts: Data collection, Unsupervised Clustering, Supervised Classification, and Web application. Fig. 1 shows the overall flow of the system.

Fig. 1. Overall flow of the system

First, a script is prepared to collect data automatically from our database, SQL server, using Perl. In our database, the raw data, which is the entire event log, is stored in chronological order in an unstructured format. To classify our data, we need to collect Data such as lot Number, Oven number, Session Number, Design ID, Step, and oven error message data from the event log. Of particular importance to our project is the oven error message data. However, this data is in an unstructured Natural Language format, posing a challenge. To overcome this, we employ the NLP technique Term Frequency-Inverse Document Frequency (TF-IDF). This technique is pivotal in transforming the Natural Language format of error messages into a more manageable vector format. However, even after this transformation, the sheer volume of data makes it challenging for engineers to categorize error messages individually.

Second, an unsupervised clustering algorithm is applied to reduce this workload and determine its approximate number of clusters. Three clustering algorithms, including k-means clustering, Density-Based Spatial Clustering of Applications with Noise (DBSCAN), and Agglomerative Clustering, are tested using Python to find the best clustering model.

Third, relevant BURN engineers help advise whether the clustering is correct and label each data set. After labeling data, supervised classification algorithms are applied to the data set. Four classification algorithms, including Support Vector Classifier (SVC), Random Forest (RF), Naive Bayes (NB), and Logistic classifier, are tested to find the best classification model. The hyperparameters are tuned to validate some models, and the best performance model is chosen.

Last, one web application is developed to let users communicate with the system in a user-friendly way. Web applications will be divided into two parts: Frontend and Backend. At Frontend side, the user fills in the required inputs to use this app. After receiving input data, the Backend side will retrieve data based on input. Then, the final disposition output with some necessary information about termination will go to the Frontend and be shown to the user.

# Result and Discussion

The proposed method in the previous session was successfully implemented to form a comprehensive system.

## Automatic Data Extraction

A Perl script is generated to automatically extract data from our server. The script extracted three years of NAND and mNAND data (2,935) from the MSB Singapore site database for the initial big data crunching stage. TF-IDF is applied to error messages to change the data format to vector format, which is input data for Unsupervised clustering.

Besides past data extraction, the system must extract fresh data in real-time to ensure accuracy. Hence, three cronjobs will be run once per day. The first one, cronjob, will temporarily query daily termination cases and save them to a file. The second cronjob will add the data from the first cronjob into the system data storage location and accumulate data to train our data for machine learning in the future. The third one, cronjob, will trigger the update/reflection of actual termination cases on the Tableau dashboard.

## Unsupervised Machine Learning

K-Means, DBSCAN, and Agglomerative models are considered to determine the best clustering model. Hyper-parameter tuning was conducted on each before the models were tested. Table 1. shows the Silhouette score and Hyperparameters. The best model is DBSCAN based on the Silhouette score. Therefore, the DBSCAN will be used for clustering.

Table 1  
Silhouette Score and Hyperparameter

|  |  |  |
| --- | --- | --- |
| Clustering  Algorithm | Silhouette  Score | Hyper Parameter |
| K-means | 0.63 | Number of Cluster = 28 |
| DBSCAN | **0.67** | **Epsilon = 0.8, minimum sample =10** |
| Agglomerative | 0.59 | Number of Cluster = 28 |

## Supervised Machine Learning

After labeling data from relevant engineers, supervised ML models are applied. RF, Multinomial NB, Logistic Regression, and SVC are considered to determine the best clustering model. Hyperparameter tuning was conducted on each model before the models were tested. After setting hyperparameters, fivefold validation is applied to each model to choose the best model based on accuracy.

Table 2  
Accuracy and Hyperparameter

|  |  |  |
| --- | --- | --- |
| Classification  Algorithm | Accuracy | Hyper Parameter |
| RF | > 0.98 | n\_estimators=200, max\_depth=30 |
| Multinominal NB | > 0.94 | alpha = 1 |
| Logistic Regression | > 0.96 | C = 1000.0, penalty = l1, solver = liblinear |
| SVC | **> 0.98** | **C = 100, gamma = 0.1, kernel = rbf** |

Table 2. shows the Accuracy and Hyperparameters. All the models have high accuracy. Among classification models, SVC is chosen as the final model for this system because it has high accuracy but also the lowest variation.

## Web Application

One web application was designed to connect the users with the ML system mentioned in the previous section through the graphical user interface (GUI). The web application was named “Disposition of Termination Assistant” (DoTA). The target users for this application are EDT and TSE teams. There are several main features have been set up in the application for EDT and TSE usage, as below:

* Termination Information Query and Disposition Advice—The system will trigger the query once the user inserts inputs Lot ID and Oven ID. The query result page contains test session information, errors with termination details, and suggested disposition as an Output.
* Email Reporting for Termination Cases – The application generates an email draft that contains session information, termination details, and a table with the basic MAM information for the terminated lot.
* Dashboard for Termination Case Analysis (Using Tableau)
* Past Cases Documentation
* AMBYX5 Legacy Devices Support

1. Conclusion

There are few gains from implementing the DoTA application. Firstly, the system helps streamline the resolution process for burn termination issues by providing first-pass resolution to EDT to improve work efficiency and reduce workload for TSE/EDT. Besides that, the TSE team can easily track the top Pareto of termination clusters or design ID with the higher number of termination cases from the Tableau dashboard so that they can investigate the issue and look for the fix more efficiently. In addition, the new TSE members can learn the dispositions for each category from the past case documentation directly without seniors’ guidance.

There are some limitations of the current DoTA project. Currently, the system does not fully support Ambyx5 due to tester and program differences and only partially supports the DRAM product or CHAMBER step. To cover up, the team will evaluate whether it is critical to support Ambyx5 products in the future since all newer/future products will use Ambyx6 ovens only. Also, the team will frequently continue to calibrate the system based on more data from different products/steps.

Acknowledgment

Deep gratitude goes first to the EDT team which helped to provide support and feedback during the system design and testing process. Appreciation also extends to NAND/mNAND TSE team members who provided dispositions for each error cluster to the project team.