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Toward Industry 4.0. in Surface Mount Technology: Smart Manufacturing in Stencil Printing Operations

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Abstract: As the foremost point of contact in surface mount technology (SMT) operations, the stencil/solder paste printer (SPP) is a major contributor to defects in the printed circuit board (PCB) assembly process. These initial defects decrease the quality and reliability of the entire system. Because of the high variation in SMT processes, a predictive, real-time machine learning (ML) algorithm that optimizes printer settings based on the estimation of printing volumes is crucial in improving overall SMT performance and process capability. Building upon existing literature, this research discusses implementing a dynamic ML model to predict optimal printing parameters and reduce changeover time within SPP processes through the training and testing of large sets of solder paste inspection (SPI) data. To sustain growing market demand, successful development and validation of a dynamic prediction system that optimizes printing parameters provide the potential for improvements in first pass yield rates and system throughput.

Keywords: Surface Mount Technology (SMT), Stencil/Solder Paste Printer (SPP), Printed Circuit Board (PCB), Machine Learning (ML), Surface Mount Assembly (SMA), Solder Paste Inspection (SPI)

1. Introduction

First developed in the 1960s, an SMT-based assembly line features a series of complex machines that work in series to secure surface mount components (SMCs) onto a PCB (Yi, 2021). The SPP controls the granular deposition of solder paste onto the PCB and is a key vulnerability for printing defects in the SMT process. For this research, the paper is specifically focused on optimizing the initial solder printing results solely with the SPP and SPI machines. The performance quality of the SPP is influenced by a variety of printer settings (i.e., stencil parameters, cleaning cycles, etc.) and environmental factors that produce complex relationships between printing results and influential parameters. While existing literature on machine learning applications in SMT operations shows promising real-world potential, a dynamic, predictive method for SPP control remains limited due to large difficulty in estimating printing performance with high accuracy and reliability.

This research focuses on optimizing the changeover time between different size PCBs by analyzing experimental SPI data acquired from a specified design of experiments (DOE) and using ML algorithms. We conduct experiments in the Smart Electronics Manufacturing Laboratory (SEML) in the Integrated Electronics Engineering Center (IEEC) at Binghamton University. All aspects of the SMT process, including experimental design, machine operation, data collection, and statistical analysis, are performed in-house. Developing an AI/ML-integrated SEM platform can significantly improve SMT efficiency and quality, providing real-time optimization techniques and statistical process control (SPC) strategies.

The rest of this document is organized as follows: Section 2 presents a literature review on SMT and prediction modeling, Section 3 introduces the experimental design and research methodology; Section 4 discusses the data collection and experimental results; importance, and future work on dynamic SMT optimization is discussed in Sections 5 and 6.

2. Literature Review

Advancements in machine learning (ML) and artificial intelligence (AI) have enabled a wide variety of industries to improve system efficiency and production quality. With a total addressable market size of over $500 billion in 2021, smart electronics manufacturing (SEM) is a rapidly growing industry that leverages SMT operations and the Internet of Things (IoT) devices to fabricate PCBs of all shapes and sizes. Within a surface mount assembly (SMA) line, a series of SMT machines work in conjunction to make this technology possible. The line consists of three major sequential processes: solder paste printing, pick & place mounting (P&P), and reflow oven heating, with optical inspection machines following the result of each process. In layman's terms, the SPP uses a metal blade (squeegee) to push solder across a thin metal stencil and onto the PCB, with the board position verifiably aligned under the stencil. As shown below in *Figure 1*, the stencil printer is the first machine in the SMA line to interact with the base PCBs and functions by controlling the granular deposition of solder paste onto the board, based on a variety of machine settings and input parameters.

Figure 1. An Illustration of the General SMA Line (He et al., 2021)

As a result, SPP performance largely affects first-pass yield rates of PCBs, observed through the analysis of inspection data from the SPI (Park et al., 2019). Inspection data used in this research are considered as sequential observations for each PCB run through the printer. For every SMT stage passed in the SMA line, defective repair costs of PCBs increase by over 500% (Wang et al., 2021). Research shows the SPP accounting for more than 50% of solder paste defects in the SMA process (Park et al., 2019), making it a vulnerability and critical bottleneck within the system (Khader & Yoon, 2018). Common types of solder paste defects include excessive/insufficient volume, offset components, bridging, and tombstoning (PCBA, 2019).

To mitigate printing defects, extensive studies have been conducted to understand correlations between printing factors and their dynamic relationships. Many confounding factors like high natural process variation and large amounts of noise in datasets degrade the integrity of experimental findings (Wang et al., 2021). However, a recent paper by Khader and Yoon mentions that the most influential factors on printing results include printer settings, cleaning cycle, printing direction, squeegee parameters, and environmental conditions like temperature, humidity, and solder paste viscosity (Khader & Yoon, 2018) (Wang et al., 2021). Printer settings such as printing speed (PS), printing pressure (PP), and separation speed (SS) are adjustable parameters whose optimal values may change depending on a variety of inputs and environmental conditions, and various optimization studies on these settings have been conducted in the past (Park et al. 2019). Relationships between printing parameters have been modeled in past research using the Neural Networks (NN), Random Forest Regression (RFR), and Support Vector Regressor (SVR) (Park et al., 2019).

To determine the optimal printer settings, nonlinear optimization models are developed, as well as online and offline machine learning algorithms to train and test predictions (Park et al. 2019). Online learning is a relatively new paradigm in which prediction algorithms are updated based on real-time system inputs and has been extensively studied in other data stream applications in the healthcare and banking industries (Park et al., 2019). These models process SPI data collected and fed to the algorithm in a specified design of experiments (DOE) (Khader & Yoon, 2018). In a recent study by Hongya Lu et al., researchers found that the offline SVR model, which learns from short-term memory feedback, demonstrated excellent offline prediction performance with R^2 values of 92% and 81% for volume averages and standard deviations (Park et al. 2019). Alternatively, the Online Sequential Extreme Learning Machine (OSELM) model showed impressive learning efficiency but had lower accuracy than SVR (Park et al., 2019). The findings emphasize the incredible potential of ML applications within SEM for robust dynamic control of SMT operations.

3. Experimental Methodology

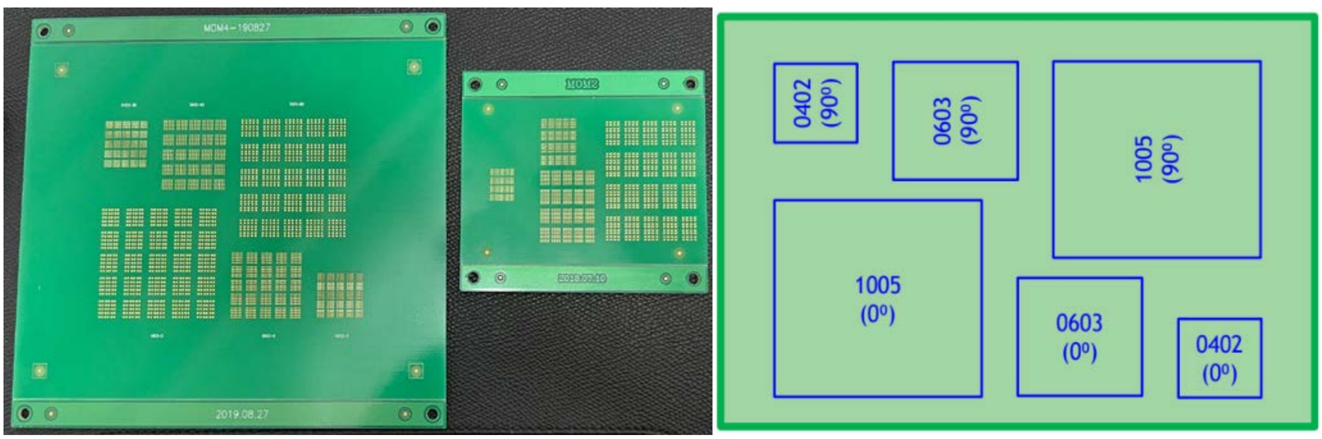
3.1 Experimental Objective

We investigate whether similar optimal printing settings can be used between different sized boards (i.e., MOM4 & MOM2) containing similar sized components (0402M, 0603M, 1005M). The SPI machine analyzes the printing results and compares them to pre-defined printing tolerance levels for the SPP and specific board type, provided in a manufacturer JOB file loaded into the machine program. By implementing offline ML strategies based on literature findings and backed by data-driven experimentation, the student team will work to develop a dynamic ML model to predict optimal printing parameters based on feedback from SPI results, functioning to optimize changeover times, minimize PCB defects, and increase throughput and first pass yield rates in the SPP.

3.2 Design of Experiments (DOE)

The research team created a set of standard guidelines and procedures to reference during experiments run in the SEML. With numerous factors affecting printing performance, the DOE is crucial in identifying correlations between parameters and minimizing external sources of error. The three significant parameters affecting overall performance the team is investigating include printing speed, printing pressure, and separation speed.

Evaluating relationships between the three parameters and their impact on printing performance is compared between MOM4 and MOM2 board type PCBs, both single-sided FR-4 (woven glass and Epoxy) PCBs. The MOM4 board has dimensions of: *Length x Width x Thickness* = 160*mm x* 150*mm x* 1*mm*, and the MOM2 board has dimensions of: *Length* $\times$ *Width* $\times$ *Thickness* = 90*mm* $\times$ 80*mm* $\times$ 1*mm*. *Figure 2(1)* on the left shows a physical comparison of the two boards placed alongside one another, and *Figure 2(1)* shows the layout positioning for each component group in the MOM4 PCB.



(1) (2)

Figure 2. (1) Photo of MOM2 / MOM4 PCBs and (2) MOM4 Component Positioning (He et al., 2021)

Testing the two different PCB dimensions with similar component pad sizes of 0402mm, 0603mm, and 1005mm allows the team to test various SPP inputs - PS, PP, and SS, and compare SPI results between experiments to identify patterns and significant parameter relationships. Other factors such as printing direction and cleaning cycle are kept constant between experiments to minimize unnecessary noise in the data and its impact on results. *Table 1* illustrates the experimental settings, materials, and specifications used in the DOE.

Table 1. DOE Specifications

Factor	Specifications
Printer Settings	PS: 45 mm/s; PP: 60 N or 6 kgs; SS: 3 mm/s
Board Type	MOM4 & MOM2
Printing Direction	Forward & Backward, Single Stroke
Squeegee	300 mm blade
Cleaning Cycle	(2) vacuum dry | (4) vacuum wet
Other	Room Temperature & Humidity

4. Results and Analysis

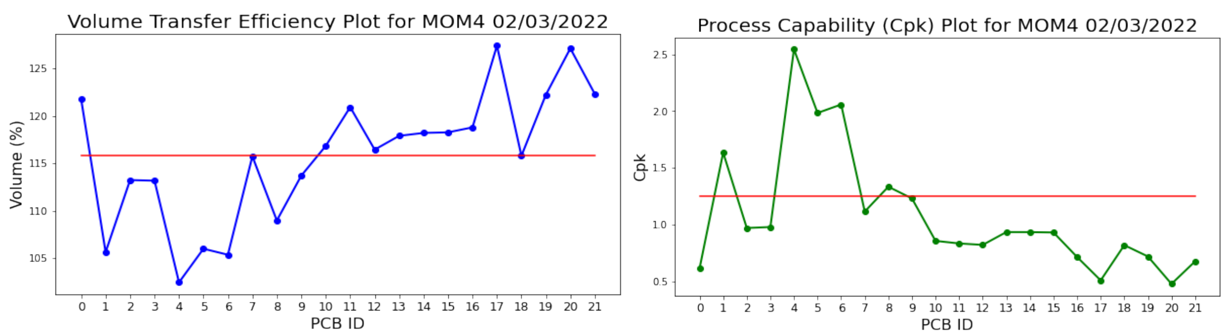
4.1 Data Collection

Experimental inspection data was collected via comma-separated values (CSV) format through a USB output from the SPI machine. The dataset consists of various parameters such as PCD IB, Pad ID, Volume (%), and Result (good, error warning, error), dealing with the SPP and its relative printing quality for each PCB run in the experiment. After downloading the data, Python and Minitab software were used to interpret the results and create data visualizations.

4.2 Statistical Analysis

Solder paste volume percentage is a direct measure of the printing process transfer efficiency and is the target metric for dynamic prediction models and standard deviation values. It is calculated by the SPI's evaluation of the inspected value for each pad component relative to the pre-defined tolerances specified by operators. In the SEML, printer tolerances between 50% and 150% are deemed acceptable; values between 50% - 75% and 125% - 150% are denoted with a warning. Values are recorded and subsequently passed or failed for each PCB run by the SPI and are used to populate the Cpk calculations, which measure process consistency relative to the target value (100%) and ability to remain within specification limits. Once more experimental data is collected with varied input parameters, the inspection results will be fed into an offline support vector machine (SVM) algorithm for supervised learning and parameter optimization.

Figure 3(1) displays a time series plot for the average volume transfer efficiency (VTE) calculated for each individual PCB in one of the team's MOM4 DOEs, and *3(2)* highlights the Cpk values for each PCB. The red lines on the figures indicate the total aggregate averages for the experiment. Based on findings, overall averages for both metrics were found to be around 116% for average VTE and 1.25 for overall Cpk, indicating high process variability. As shown in *Figure 3(2)*, only 5 of the 22 boards in this experiment had Cpk values above 1.33, the general industry standard. Average values over 100% indicate excessive solder paste deposition, which can lead to downstream printing errors in SMT processes such as solder bridging and tombstoning. These errors incur high manufacturing costs and material waste if left untreated, further emphasizing the importance of stable, high-performance SMT processes.



(1) (2)

Figure 3. (1) Average Volume (%) for MOM4 DOE & (2) Cpk Plot for MOM4 DOE

Pareto analysis was conducted using Minitab to identify the relative defect distribution observed from the DOEs. Prior to computation, SPI data for the 0402M pad components were removed in an effort to reduce noise, as the smallest size components have naturally high defect levels regardless of experimental settings. The "E classifies an inspection error." and a warning is classified by the "W." *Figure 4(1)* highlights the most frequent inspection errors seen in one of the MOM4 DOEs, in which 60% of the results were classified as "GOOD."

Insufficient/excessive solder paste warnings attribute 19% and 6.8% of the remaining dataset, respectively, with "E.Bridging" accounting for 6.3% of defects. Bridging is a positional error where solder may overlap two different pads on the PCB, leading to short-circuits during operation. *Figure 4(2)* displays the results of an Anderson-Darling normality test run on the inspection results distribution. Since the calculated *p*-value of 0.072 is greater than the significance level of the alpha value (0.05), the test fails to reject the null hypothesis, indicating a non-normal distribution with high skewness and kurtosis.

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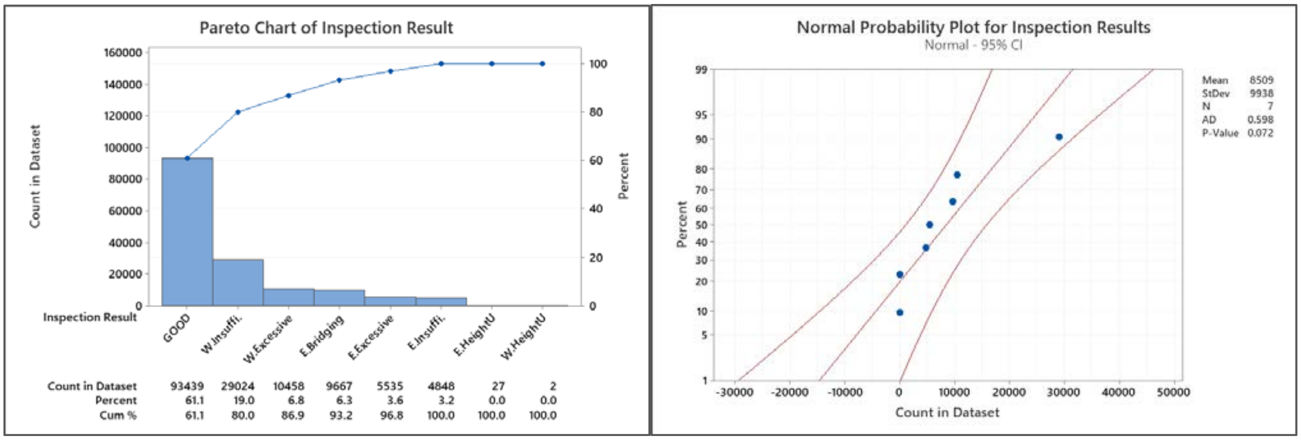

(1) (2)

Figure 4. (1) Pareto Analysis of Inspection Results & (2) Anderson-Darling Probability Plot for MOM4 DOE

5. Discussion

With the high complexity and variability of SMT operations in electronics manufacturing, developing new methods and best practices to improve process capability is vital for real-time quality control measures. Finding software solutions that mitigate risks across boards with a constant aperture setting/aspect ratio allows for high-impact production throughput and yield standards to be met. In a production process of high-mix, low-volume (HMLV) products, it can take hundreds of PCBs to be printed and inspected before quality parameters can be determined (Kocsi et al., 2020). It poses a threat to other companies in the market and often raises questions about the reliability of processes and deliverables (Kocsi et al., 2020). However, with the assistance of an intelligent software system capable of evaluating real-time data from the SPI, an optimization model for the printing process can be formulated to suggest optimal parameters, saving time, and reducing the changeover rate (CR) between various PCBs.

Specifically, CR is the rate at which a system can effectively and efficiently alter machine settings and process control requirements from one product to another until a qualifying product is achieved (Lee et al., 2017). In an HMLV environment, having a high CR is essential to attain a competitive edge within an emerging market. Low CR is subject to higher costs, dysfunctional scheduling, low productivity, and quality-control issues (Kocsi et al., 2020). The ability to conduct a swift changeover between alternate PCB types provides increased quality performance and cost reduction benefits, allowing manufacturers to allocate resources towards further process advancements. Leveraging new technologies and tracking key performance metrics is necessary for improving SEM processes.

Moving forward with the team's machine learning strategy, a low-code Python package called PyCaret will be implemented as more experimental data continues to be collected. PyCaret evaluates datasets with multiple algorithms simultaneously, automating workflows and highlighting the most accurate and precise algorithms in terms of target parameters. This package reduces the amount of code needed for conventional ML analysis during the underwriting process, allowing the team to leverage multiple algorithms, calculation metrics, and data visualizations more quickly.

The use of AI/ML and Industry 4.0 methodologies to optimize the SMA processes has the potential to significantly improve existing SMT operations in terms of yield and throughput. Industry 4.0 introduces an SEM paradigm where machine-to-machine (M2M) interaction takes place, using advanced, interconnected computational power to improve product quality, productivity, sustainability, and cost reduction techniques (Wang et al., 2018). An intelligent software platform can provide actionable predictions based on current SPP inputs and outputs along with historical data. These insights allow for the optimization of manufacturing controls to reduce changeover time, increase throughput, and improve printing quality. Ultimately, an intelligent system will allow further advancements to be made in SEM operations toward streamlining SMA processes. A true end-to-end system integration highlights the future vision of an interconnected, robust, and resilient smart manufacturing system.

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6. Conclusion

With the high demand for electronic components and the maturity of SMT within electronics manufacturing, one of the essential foundations is process reliability (Yi, 2021). To reduce defects on the SMT line, increases in experimental research & development allow for the planning, testing, and implementation of innovative AI/ML solutions. With the rapid growth of PCB usage in the SEM industry, precision and accuracy are of the utmost importance in optimizing printing parameters. By collecting and analyzing inspection data from the SPI, a smart system interface can be constructed to predict SPP defects in real-time and suggest optimization parameters to minimize errors. A solution to the high defect rates evident in SMT processes is valuable to the future development and optimization of the SMT line. As components continue to decrease in size, this research aims to model the real-time factors influencing SPP performance by developing dynamic prediction models. A system for identifying changes in real-time data and improving the accuracy of ML algorithms in the presence of noise and natural process variation is a critical focus area in increasing the performance of dynamic prediction modeling for manufacturing processes. In the future work of this research, combining online and offline ML algorithms can potentially improve noise filtering and adaptiveness of dynamic SPP control.

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