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Automated Semiconductor Packaging Simulation Model

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Author Note: Jason Chernyak, Andrew Occhi, Bryan Blair, Gino DeLeone, Madison Adams, and Mikayla Beauregard are all fourth-year seniors at SUNY Binghamton's Watson College of Engineering, pursuing degrees in Industrial and Systems Engineering. Dr. Mark Poliks supervises this senior capstone project, with advisement from Dr. Fuda Ning and Dr. Yingge Zhou. For any questions, comments, or concerns, contact the email above.

Abstract: This project develops a comprehensive semiconductor packaging simulation model for Universal Instruments, optimizing workflow efficiency and evaluating automation potential. The model simulates key production stages including wafer cutting, die placement, adhesive curing, and final panel assembly, while targeting an annual output of 8.8 million placements per year. By using ARENA simulation software, the study analyzes capacity, staffing requirements, and process variability to enhance production scalability. A primary focus is assessing the impact of semi- and full automation on throughput, labor allocation, and cost efficiency. The project integrates industry standards, and data-driven decision-making to propose an optimized workflow for Universal Instruments' new facility. Findings will inform strategic investments in automation, ensuring improved productivity, reduced scrap rates, and a streamlined manufacturing process. This work advances semiconductor packaging efficiency through simulation-driven analysis and operational enhancements.

Keywords: Simulation, Resource Allocation, Economic Order Quantity

1. Introduction

Universal Instruments' semiconductor packaging simulation model project aims to develop a comprehensive digital representation of the entire production workflow, from inventory management to packaging. The production site produces circuit boards of varying quantities of semiconductor placements, and we were tasked to focus purely on the 414 placement board. The scope encompasses modeling production, altering staff/machine quantities and scrap rate to reach a targeted production of 8.8 million placements per year. The simulation will capture the manufacturing process, including laser dicing of solar cells, wafer pickup, substrate preparation, die placement, adhesive curing, silicone application, and glass integration.

To meet the growing demand from its customers, Universal Instruments is working to upscale its semiconductor packaging line. Currently, production is being conducted in a laboratory setting where various manufacturing parameters are being tested. Once the desired parameters and equipment are finalized, production will transition to the main floor, where Universal Instruments has allocated space for assembling a new production line. At the moment, the proposed production setup is not operating at the desired efficiency, which poses a risk of lost revenue and strained partnerships if throughput is not improved.

To address this challenge, the project will develop an accurate and comprehensive simulation model of the proposed semiconductor packaging line. This model will help assess the feasibility of achieving the annual production goal of 8.8 million placements while optimizing key operational parameters, such as process efficiency, scrap rate reduction, and staffing requirements.

2. Methodology

The semiconductor packaging simulation model is developed using a combination of engineering methodologies to ensure accuracy and reliability. The primary tool for this project is Arena software, which will be used to create a detailed simulation of the production line. Input parameters such as production rate, cycle times, scrap rate, and equipment capacity will be incorporated to generate a realistic model. A Design of Experiments (DOE) approach will be applied to determine optimal process configurations, utilizing either full or fractional factorial designs depending on the complexity of the system.

Simulation results will be validated against hand calculations and real-world data from Universal Instruments to confirm model accuracy. An Economic Order Quantity (EOQ) model will be implemented to optimize inventory management, ensuring stable material availability while minimizing costs. A staffing analysis will also be conducted to determine labor requirements under different automation scenarios, helping Universal Instruments make informed decisions about workforce allocation.

2.1 Arena Model Creation

There are four phases in the overall process, with three prep phrases being performed in parallel and feeding into final fabrication. The substrate prep phase is combined with final fabrication in Figure 2.1.1.

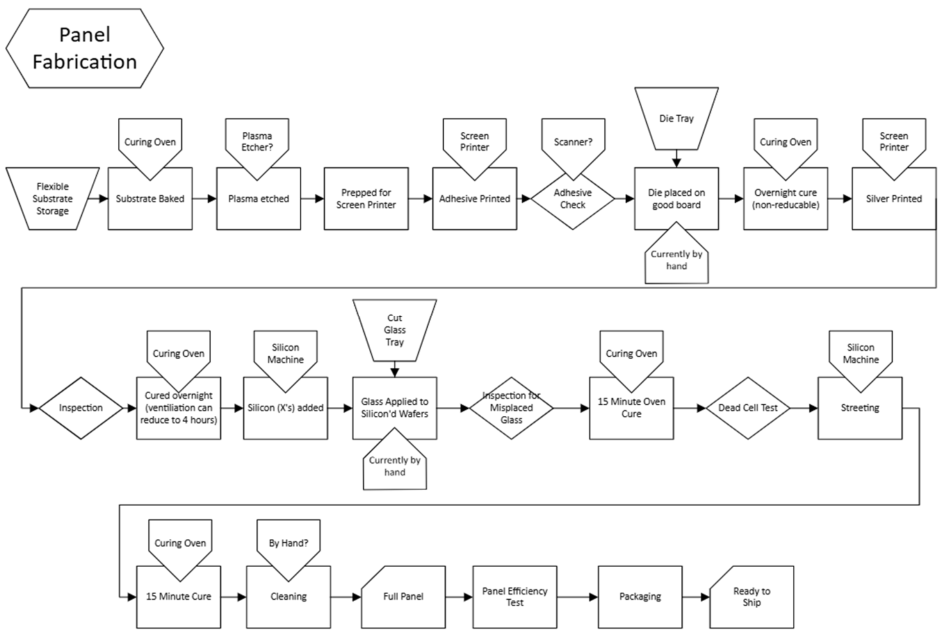

Figure 2.1.1 - Substrate Preparation and Panel Fabrication Stage

These process flows were used to construct the logic of the Arena model. Timing information for process steps and material transport was provided by Universal Instruments, while machine and worker capacity were determined by a site visit to Universal. Further site visits, initial testing, and revised process times revealed that the wafer and glass prep processes were not limiting the process output and would be kept wholly separate in terms of staffing and materials. As such, a streamlined version of the arena was created, as seen in Figure 2.1.2.

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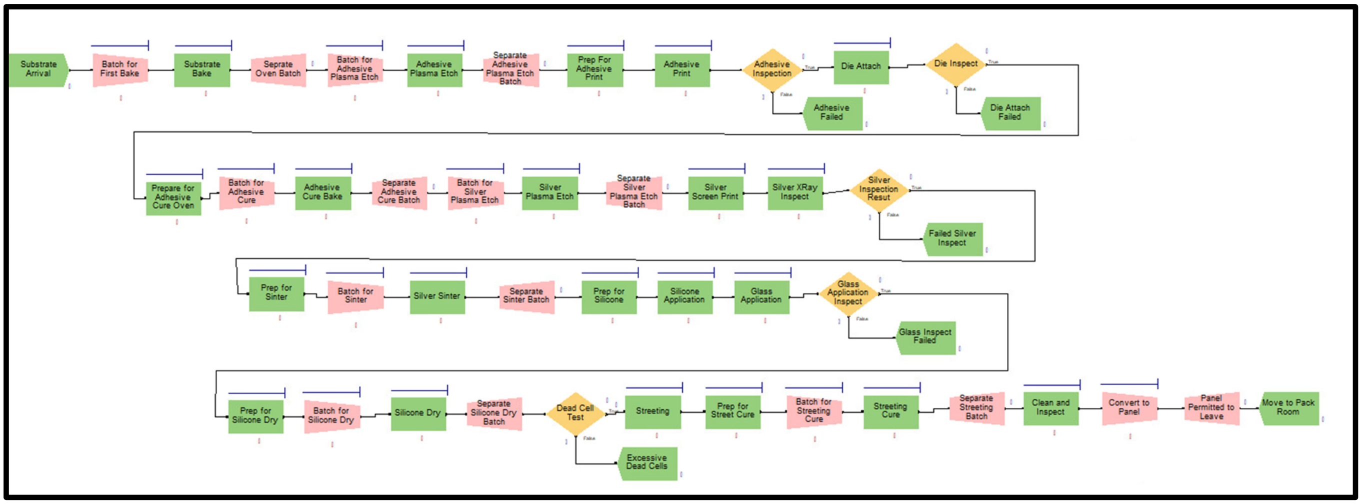

Figure 2.1.2 - Experimental Arena Model

2.2 DOE and Arena Results

A Design of Experiments was developed for three initial factors of interest - the number of workers, the total scrap rate, and the number of GPD machines. The specific levels for each factor are presented in Figure 2.2.1 in accordance with Universal Instruments' predefined ranges and values. A full factorial experiment was created with these factors, with the resultant fifty-four runs being feasible due to the short amount of time required to run them in Arena. The replication parameters for each run can be seen in Figure 2.2.2.

Factor	Level					
	1	2	3	4	5	6
Staff #	9	10	11	12	13	14
GPD #	1	2	3			
Scrap Rate	10%	20%	32%			

Figure 2.2.1 – DOE Factors and Levels

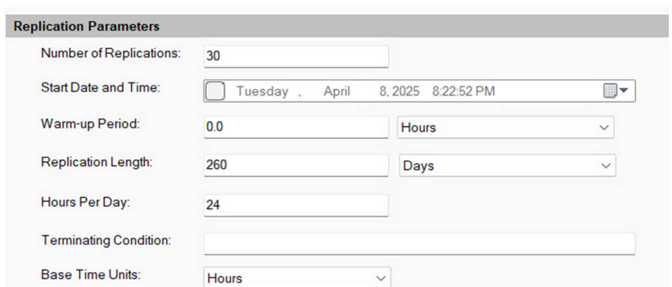

Figure 2.2.2 - Replication Parameters

The results from the experimental runs were analyzed using a multivariate linear ANOVA in Minitab. In particular, the relationship between the factors and instantaneous worker utilization and panels produced were examined. As can be seen in Figures 2.2.3 and 2.2.4, all three factors did have a significant effect on worker utilization. The F-value of the ANOVA and high difference of means in the main effects plot imply that the most significant factor was the number of workers, confirmed by a Tukey test demonstrating that all treatments are significantly different. While the main effects plot appears to show that 2 GPD machines results in a higher mean than 3, the Tukey test shows that there is not a significant difference between the two. When analyzed in conjunction with the scrap rate, which also results in a significantly different value for each level, the optimal number of workers and GPD machines to maximize utilization is dependent on the scrap rate.

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Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Worker Coding	5	0.010255	0.002051	169.93	0.000
Scrap Coding	2	0.001017	0.000509	42.15	0.000
GPD Coding	2	0.000375	0.000188	15.55	0.000
Error	44	0.000531	0.000012		
Total	53	0.012178			

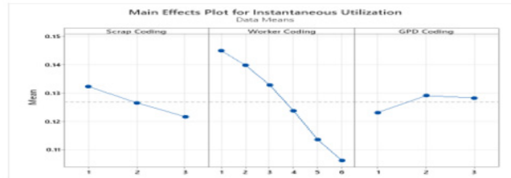

Figure 2.2.3 - ANOVA Results and Main Effects Plot for Instantaneous Utilization

Grouping Information Using the Tukey Method and 95% Confidence

Worker Coding	N	Mean	Grouping
1	9	0.144778	A
2	9	0.139676	B
3	9	0.132760	C
4	9	0.123581	D
5	9	0.113462	E
6	9	0.106145	F

GPD Coding	N	Mean	Grouping
2	18	0.129005	A
3	18	0.128159	A
1	18	0.123038	B

Scrap Coding	N	Mean	Grouping
1	18	0.132183	A
2	18	0.126456	B
3	18	0.121563	C

Means that do not share a letter are significantly different.

Figure 2.2.4 - Tukey Test for Instantaneous Utilization

Similarly to the results for the utilization, all three factors were determined to be significant in the ANOVA for the number of panels produced. The main effects plot shows a greater difference between the scrap rates as compared to utilization, confirmed by the interaction plot showing far steeper lines. The Tukey test shows that, despite what appears to be a higher mean production for level four of the worker staffing factor, levels three through six do not differ significantly, and again neither do levels two and three of the GPD coding. The ideal number of workers and GPD machines is again shown to be dependent on the observed scrap rate.

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Worker Coding	5	18311552	3662310	27.01	0.000
Scrap Coding	2	9601875	4800937	35.40	0.000
GPD Coding	2	4260266	2130133	15.71	0.000
Error	44	5966786	135609		
Total	53	38140478			

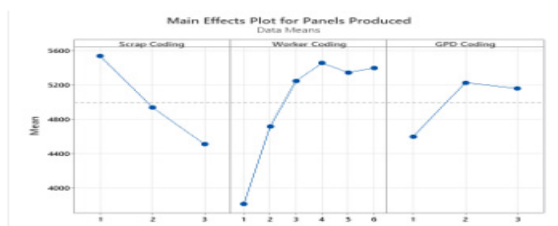

Figure 2.2.5 - ANOVA and Main Effects Plot for Panels

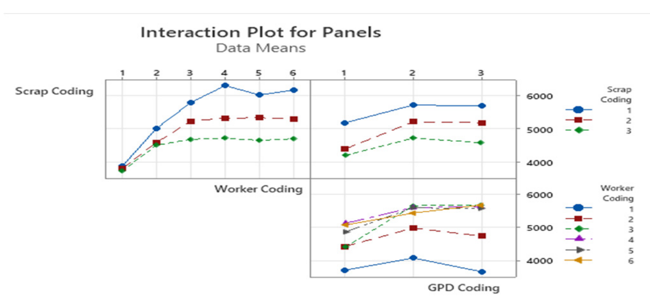

Figure 2.2.6 – Interaction Plot for Panels

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Grouping Information Using the Tukey Method and 95% Confidence

Worker Coding	N	Mean	Grouping
4	9	5452.59	A
6	9	5395.04	A
5	9	5343.41	A
3	9	5244.37	A
2	9	4712.46	B
1	9	3811.02	C

Scrap Coding	N	Mean	Grouping
1	18	5535.45	A
2	18	4936.83	B
3	18	4507.17	C

GPD Coding	N	Mean	Grouping
2	18	5224.26	A
3	18	5157.39	A
1	18	4597.81	B

Means that do not share a letter are significantly different.

Figure 2.2.7 - Tukey Tests

2.3 Interpretation and Recommendations

From these results it can be concluded with reasonable confidence that staffing and capacity guidelines to maximize worker utilization and panel production, thus minimizing labor costs, are a function of scrap rate. Results demonstrate that for panel production at a 32% scrap rate, 11 workers and 2 GDP machines are optimal, at a 20% scrap rate 11 workers and 3 GDP machines are, and at a 10% scrap rate 13 workers and 2 GDP machines are. For utilization, at all scrap rates 9 workers and 2 GPD machines are optimal. It can then be reasonably concluded that it is always optimal to use only 2 GPD machines, as there is no significant difference between the groups present amongst optimal production factor configurations and each additional machine will incur significant costs. Table 2.3.1 breaks down the percent loss in productivity when optimizing utilization and percent loss in utilization when optimizing productivity against both scrap rate and staffing difference. The financial information for cost per staff and profit per panel is only internally available to Universal Instruments, but a decision of whether it is financially better to optimize production or not for each scrap rate can be easily made by the team using the simple formulas provided below Table 2.3.1. Unfortunately, no reasonably accurate regression equation could be identified, but the categorically identified scrap rates may still be used as points to round to based on an analyst's best judgement when evaluating an observed scrap rate not equal to one of the three explored.

		Panels Produced	Utilization	% Loss in Productivity	% Decrease in Utilization	Difference in Staff
32% Scrap Rate	*Prod Optimal*	5025	0.129		11.92%	2
	Util Optimal	4075	0.147	18.90%		
20% Scrap Rate	*Prod Optimal*	5847	0.138		6.03%	2
	Util Optimal	4047	0.147	30.80%		
10% Scrap Rate	*Prod Optimal*	6441	0.122		17.69%	4
	Util Optimal	4090	0.148	36.49%		

Table 2.3.1 - Losses Against Optimized Factor Combinations

$$At\ S = 32\%;\ if\ .189n_p * P_p > 2 * C_w, optimize\ productivity$$

$$At\ S = 20\%;\ if\ .308n_p * P_p > 2 * C_w, optimize\ productivity$$

$$At\ S = 10\%;\ if\ .3649n_p * P_p > 4 * C_w, optimize\ productivity$$

where S = scrap rate, n_p = number of panels produced per unit time, P_p = profit per panel and C_W = total cost per worker per unit time

2.4 EOQ

An Economic Order Quantity (EOQ) is an equation that allows companies to determine the optimal inventory policy so that demand is met while minimizing costs. Universal Instruments expressed interest in having our team develop an EOQ model for several raw materials that are vital to the semiconductor fabrication process; they are adhesive, silicone, silver, and dicing tape. The company noted that there was not currently a standardized procedure for the ordering of these materials, which is what led the group to construct this model. The team was provided with unit costs, usage rates (used to determine daily demand), and lead times for these materials. Using this data, we created a flexible EOQ model. The EOQ uses the initial inputs for the unit cost of the material, the usage rate per panel, the current demand, the setup cost per order, the holding cost, and the lead time in days, but the model is dynamic and allows for these values to be changed. The values can be changed because Universal Instruments informed us that they plan to increase production in the future, which would affect the demand. Additionally, the unit costs of these materials are also volatile and therefore are subject to change. The exact figures for setup and holding costs for these materials were not available, so we inferred them. They can be changed later to reflect the exact figures the company comes up with once the model is handed over to Universal Instruments. The team inferred the holding costs based on industry data from Fabrikator and Netstock, but these placeholder values can be adjusted to the correct values when Universal Instruments finishes their calculations. Once these values are input, the model will then return a statement with the calculated order quantity and reorder point letting the company know what their inventory policy should be for that material.

3. Conclusions

The development of a semiconductor packaging simulation model for Universal Instruments represented a critical step in optimizing the efficiency and scalability of their manufacturing process. By utilizing the ARENA simulation software and considering factors such as staff distribution, scrap rate, and machine quantity the project aimed to upscale production working toward their annual goal of 8.8 million placements. Findings provided actionable recommendations for the number of staff and GPD machines in support of increasing market demands and advancing manufacturing capabilities.

Additionally, the team developed an EOQ model that was sent to Universal Instruments so they will be able to access these numbers after the project completion. The prices of these materials were volatile, and were subject to change at any time, as were the other variables that went into these calculations. By having access to this model, it will allow Universal Instruments to change the numbers at any time, which will enable them to make necessary adjustments for whatever issues they might face at any moment, whether it is something internal such as a change in holding costs, or external such as a change in the lead time for a certain material.

4. References

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