Proceedings of the International Conference on Industrial Engineering and Operations Management
Publisher: IEOM Society International, USA DOI: 10.46254/NA10.20250202
Published: June 17, 2025

Dynamic Simulation Tool for Analysis of the Effects of Man-Machine Ratio on Test Manufacturing Productivity of a Semiconductor Company

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Abstract

A study was conducted on one of the leading semiconductor companies worldwide, focusing on its semiconductor units' testing process. To measure its testing area's performance, the company analyzes its established man-machine ratio (MMR) using the following metrics: Overall Equipment Effectiveness (OEE), average production cycle time, operator utilization, and the total number of units produced. Currently, the company uses static spreadsheet computations in its analysis. Still, the current method cannot capture the actual scenario of their processes, such as waiting times, queueing, and the random occurrence of machine downtimes. The aim was to develop a dynamic simulation tool that can capture the actual scenario, which will then be used for MMR analysis. Using Flex Sim, a dynamic simulation model of the testing area was developed. After performing simulation runs, the current MMR of 1:5 was analyzed using the different metrics. The resulting model also developed features in which various changes within the system were performed, allowing the company to predict the possible outcomes of those changes. These changes include changing the current MMR, changing the input values, and monitoring the system's performance across time.

Keywords
Man-machine ratio, Overall Equipment Effectiveness, Semiconductor industry, Dynamic simulation

1. Introduction
A leading semiconductor manufacturer is known for its products such as amplifiers, audio products, switches, and sensors. It has a testing area for semiconductor units. Here, units were tested on machines subjected to three different temperatures designated as temperatures 1, 2, and 3. Semiconductor units were tested in lots wherein each lot consists of 4,000 to 25,000 units. To analyze the performance of the testing area, the semiconductor company analyzes its current man-machine ratio (MMR) through the use of a static spreadsheet simulation. The MMR analysis consists of the following performance measures: Overall Equipment Effectiveness (OEE), average production cycle time, operator utilization, and total output. Within their analysis, different factors were considered, such as the occurrence of machine

downtimes, operator break times, the arrival of lots, waiting times, and the different lot sizes processed by the machines. The company was looking forward to developing a dynamic simulation model that could help capture the events happening in the actual scenario, such as the randomness of machine downtimes and the waiting times due to evident queueing, given that an operator has to attend to more than one machine. Additionally, the dynamic simulation model can help monitor the performance of the testing area with respect to time and help predict the possible implications of any changes applied to the system.

1.1. Objectives

- Develop a simulation model that captures the actual scenario in the testing area of the semiconductor company
- Analyze the MMR through the use of the different metrics: Overall Equipment Effectiveness (OEE), average production cycle time, operator utilization and the number of units produced.
- Determine the features of the model that can perform different changes within the system.

2. Literature Review

Simulation techniques are widely applied to enhance efficiency and optimize processes in the field of manufacturing and production. Zhu et al. (2020) used eM-Plant software to simulate a train wagon assembly line, identifying inefficiencies and applying industrial engineering methods like 5W1H and Eliminate, Combine, Rearrange and Simplify (ECRS), which improved line balance and reduced labor requirements. In aircraft manufacturing, Zheng et al. (2024) employed simulation with model-based systems engineering and semantic technology to optimize design-phase performance. Simulation also benefits agriculture, as shown by Mauget et al. (2020), who used crop modeling to evaluate yield management options for dryland cotton in the Southern High Plains, identifying lower plant density and earlier planting as the most effective strategies. Optimizing the man-machine ratio (MMR) is key to boosting productivity. Abdullah and Rodzi (2011) found that low MMR in semiconductor manufacturing led to underutilized labor, recommending an increase from 1:3 to 1:5 and the removal of non-value-adding activities. Ghosh (2024) analyzed garment industry MMR, demonstrating that reducing over-processing improved profitability by lowering indirect costs. Ahmed (2021) applied line balancing in clothing production, resulting in better operator utilization and increased efficiency. Overall, industries aim to optimize their MMRs by streamlining processes, removing waste, and enhancing productivity through proper labor and machine utilization.

3. Methods

Dynamic simulation represents the system as it evolves or changes over time. Unlike the spreadsheet-based computations currently employed in the company, changes or other events happening within the system are taken into account, such as waiting times involved in their sequential processes, the arrival of semiconductor units, and the randomness of the occurrence of machine downtimes (Smith & Sturrock 2024). Additionally, dynamic simulations are also considered economically advantageous in some cases, depending on the approach. This is because it allows for the forecasting of future states of the system (Cremonese et al.2018), such as cycle time, operator utilization, and proportions of machine downtimes. In this study, the software used for dynamic simulation is FlexSim. It has been used in numerous simulation studies involving both regular and flexible production systems (Tikasz et al. 2012).

The general procedures for the study are presented in Figure 1. The company provided the data sets necessary for the modelling process. Stakeholder feedback was gathered during the development of the model, particularly when changes were made in the model so that it captures relevant events within the testing area. Various metrics preferred by the company for their MMR analysis are likewise identified and incorporated. Once the model is completed, results were analyzed to ensure that the model reliably estimate the system's performance

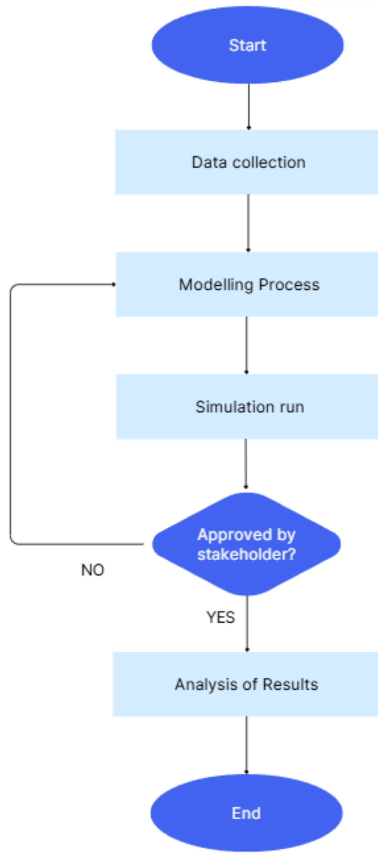

Figure 1. Methodological flowchart

3.1. Inputs and Assumptions

The current machines in the testing area comprise 29 machines with three different temperatures. This machine configuration includes 16 for Temperature 1, 8 for Temperature 2, and 5 for Temperature 3. The testing process occurs sequentially: Temperature 1 first, followed by Temperatures 2 and 3. Additionally, lots can proceed to any available machine given that it still follows the sequential manner of the testing process. There were different tagging statuses for the machines. Within each status, an operator performs a series of external tasks while the automated testing process is ongoing. Below are the different machine statuses and their definitions:

- SETUP = This includes loading units in the machine and checking for fixtures. The operator performs these tasks.

- USE = Here, the machine is running and performing the testing process itself. While this is taking place, an operator is performing a series of external tasks. These include monitoring yield, assisting, recording, and manual visual inspection. These tasks are performed on a per-lot basis.

- PACK = This mainly includes lot packing after the testing process of the units. An additional task performed in this status is printing the test summary.

- QA = The operator performs this task. This involves checking and verification of the lots.

- RESCREEN = This is basically the same as the USE status. The difference is that this process is performed on items that initially failed the testing process. Here, they are being retested before being shipped out.

Within the processing stages, planned and unplanned downtimes are common occurrences in the manufacturing area. Below is a list of planned and unplanned downtimes and their descriptions. Additionally, two non-value-adding occurrences were listed in the table.

Table 1. List of planned and unplanned downtimes happening in the manufacturing area.

Downtime	Type
Handler related breakdown	Unplanned
Isolation, verification of setup, waiting for fixture	Unplanned
Site yield-to-yield issues	Unplanned
Waiting for handler	Unplanned
Test system related downtime	Unplanned
Defective hardware	Unplanned
Defective contactor	Unplanned
Defective board/board performance	Unplanned
System/board/setup issues attended by ICT	Unplanned
Cleaning and housekeeping.	Planned
Equipment calibration	Planned
A meeting for operators was being conducted.	Non-value adding
Machine was waiting to be attended by the operator	Non-value adding

The different types of downtimes were established by the semiconductor company. Also, both of the non-value-adding types of downtimes were considered as necessary activities. Once a machine experiences an unplanned downtime, a technician will then attend to and address the problem. Downtimes per instance were computed using the formula for the mean time to repair (MTTR):

Equation 1:

$$MTTR = \frac{Total\ failure\ time}{number\ of\ failures}$$

The values for MTTR were applied for all unplanned downtimes and the operators' meeting. The mean time between failures (MTBF) applied for all the unplanned downtimes, the equipment calibration and downtimes, and one non-value adding downtime (i.e., meeting for operators was being conducted) was computed using the formula below:

Equation 2.

$$MTBF = \frac{Total\ number\ of\ operating\ hours}{number\ of\ failures}$$

The time between failures was assumed to follow an exponential distribution since it pertains to the chances of other machine failures (Jardine and Tsang, 2013).

The Overall Equipment Effectiveness (OEE), in the case of the semiconductor company, is a product of four key components: Availability, operational efficiency, quality rate, and unit per hour (UPH) efficiency. These components are measured per machine temperature. *Availability* is the proportion of the overall production time when the machine is available or running. Here, all types of downtimes were considered, including the planned downtimes such as housekeeping and cleaning, as well as the non-value-adding activities. *The operational efficiency* is the proportion wherein the machines are under the USE, QA, and RESCREEN statuses while all downtimes are being disregarded. An additional state was accounted for this metric which is the engineering assistance. For the *quality rate*, the USE, QA and RESCREEN statuses are the only ones being considered. The value computes the proportion of the machine under the USE and QA statuses. Lastly, for the *UPH efficiency*, the parameters being considered are the processing time of the machines, which is basically the USE status, and the occurrence of stoppages in the form of waiting times. The formulas for calculating each component are as follows:

- Availability = $\frac{Equipment\ Uptime}{Overall\ Equipment\ Runtime}$

  Wherein:

  Equipment Uptime = SETUP + USE + QA + RESCREEN + PACK + non-value adding downtimes + engineering assistance

  Overall Equipment Runtime = Equipment Uptime + all unplanned downtimes + all planned downtimes

- Operational Efficiency = $\frac{USE+RESCREEN+QA}{Equipment\ Uptime}$

- Quality Rate = $\frac{USE+QA}{USE+RESCREEN+QA}$

- UPH Efficiency = $\frac{EARNED\ HOURS}{TOTAL\ PRODUCTIVE\ TIME}$

  Wherein:

  EARNED HOURS = (1/UPH)*Lot Size

  TOTAL PRODUCTIVE TIME = ((1/UPH)*Lot Size) + total waiting times

4. Results and Discussion

4.1. Base Model and Its Features

Upon integration of the necessary inputs, a dynamic simulation model of the manufacturing area of the semiconductor company was developed as shown in Figure 2 below.

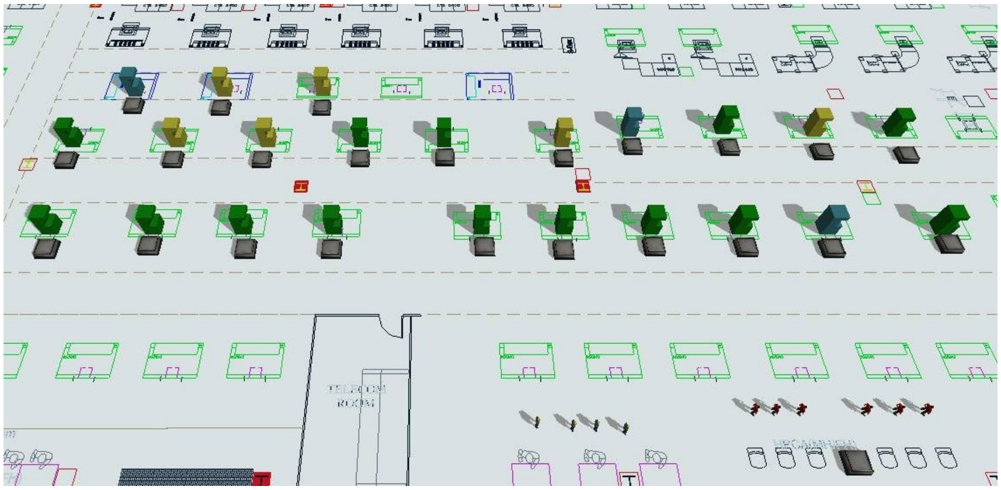

Figure 2. The Base Model

In Figure 2, the resulting model shows the current setup of the testing area: the machines of three different temperatures, the operators, and the technicians. Additionally, an AutoCAD layout of the testing area was integrated into FlexSim. The model has a current MMR of 1:5. Each machine temperature was distinguished by different colors. The green ones serve as the machines under Temperature 1, the lighter green ones for Temperature 2, and the blue ones for Temperature 3. Each machine has its designated queues, which were represented by the boxes in the figure. They were used to represent buffers once the machines had finished the testing process of semiconductor units before proceeding to the next machine. The box on the lower right serves as the starting point, wherein operators pick the lots to be loaded on machines under Temperature 1. The resulting model serves as the base model, which was then subjected to validation.

Compared to their current spreadsheet-based tool, the developed model has features useful for the semiconductor company. These features will also be valuable when the company wants to test changes in the system. Among the capabilities of the model are (a) monitoring the system across time, (b) testing changes in MMR, and (c) testing changes in input values. During the simulation run, the semiconductor company can monitor the entire system as it continues to run within a given time. In this way, the company can monitor the performance of the system in terms of their established metrics using the dashboard feature of FlexSim.

Figure 3. Dashboard showing the OEE and its components for each machine temperature

4.2. Validation

Before more analyses were performed, the model was first validated. The model was run with 20 replicates. Replication involves generating comparable outcomes with varied data and carrying out the same analysis. Validation was performed by comparing the base model and an actual dataset consisting of the company's performance results for one particular work week. These were compared to the model's results in FlexSim.

Table 2. Comparison table of the actual and simulated values

Performance Measures	TEMPERATURE 1			TEMPERATURE 2			TEMPERATURE 3		
	Actual	Simulation	%Error	Actual	Simulation	%Error	Actual	Simulation	%Error
Availability (%)	91.90	90.55	1.47	87.70	85.95	2.00	93.60	91.50	2.24
Operational Efficiency (%)	95.60	92	3.77	89.30	85	4.82	88.60	87	1.81
Quality Rate (%)	98.60	98	0.61	97.80	98	0.20	98.10	99	0.92
UPH Efficiency (%)	95.50	96	0.52	84.40	91.80	8.77	99.10	94.90	4.24
OEE (%)	82.80	78.85	4.77	64.60	65.50	1.39	80.60	74.20	7.94
Operator Utilization (%)	95	90.1	5.16	95	90.1	5.16	95	90.1	5.16
Average Cycle Time (hours)	31.50	33.48	6.29	14.40	14.63	1.60	8.40	8.86	5.48

Comparing the results obtained from the provided dataset and those generated by FlexSim, most deviations are within 5%, while a few exceeded 5% but less than 10%. The difference accounts for the complexities involved in developing the simulation model. These complexities may stem from factors such as variations in input parameters, assumptions made in creating the model, and potential discrepancies in real-world data versus simulated outcomes. Overall, the results suggest that the base model was able to mimic the expected performance of the current system. With this, the model can be said to be ready for use in crucial analysis.

4.3. Change in the MMR

A vital feature of the model that the company can tap is testing the impact of changing the current MMR. For instance, the semiconductor company can use this model when they decide to increase the MMR to 1:6 while being constrained to the current number of machines available at the testing area. This new MMR configuration incorporates a revised machine temperature mix. This feature can help the company predict the possible effect on the system in terms of its established metrics before applying this change in the actual scenario. The summary of the predicted results is presented in the table below.

Table 3. Comparison table between the base model and an MMR of 1:6

<table>
<tr><th rowspan="2">PERFORMANCE MEASURES</th><th colspan="3">BASE MODEL</th><th colspan="3">MMR of 1:6</th></tr>
<tr><th>Temperature 1</th><th>Temperature 2</th><th>Temperature 3</th><th>Temperature 1</th><th>Temperature 2</th><th>Temperature 3</th></tr>
<tr><td>Availability (%)</td><td>90.55</td><td>85.95</td><td>91.50</td><td>90.85</td><td>86.10</td><td>88.20</td></tr>
<tr><td>Operational Efficiency (%)</td><td>92</td><td>85</td><td>87</td><td>92</td><td>84</td><td>87.05</td></tr>
<tr><td>Quality Rate (%)</td><td>98</td><td>98</td><td>99</td><td>98</td><td>98</td><td>99</td></tr>
<tr><td>UPH Efficiency (%)</td><td>96</td><td>91.80</td><td>94.90</td><td>90.70</td><td>77.10</td><td>94.90</td></tr>
<tr><td>OEE (%)</td><td>78.85</td><td>65.50</td><td>74.20</td><td>74.15</td><td>54.85</td><td>71.80</td></tr>
<tr><td>Cycle Time (hours)</td><td>33.48</td><td>14.63</td><td>8.86</td><td>36.76</td><td>17.16</td><td>9.12</td></tr>
<tr><td>Operator Utilization (%)</td><td colspan="3">90.10</td><td colspan="3">96.35</td></tr>
<tr><td>Total Cycle Time (hours)</td><td colspan="3">56.97</td><td colspan="3">63.05</td></tr>
<tr><td>Units Tested (in millions)</td><td>1.24</td><td>1.24</td><td>1.22</td><td>1.11</td><td>1.12</td><td>1.10</td></tr>
<tr><td>Overall Availability (%)</td><td colspan="3">89.40</td><td colspan="3">89</td></tr>
<tr><td>Overall Operational Efficiency (%)</td><td colspan="3">89.05</td><td colspan="3">88.70</td></tr>
<tr><td>Overall Quality Rate (%)</td><td colspan="3">98</td><td colspan="3">98</td></tr>
<tr><td>Overall UPH Efficiency (%)</td><td colspan="3">94.90</td><td colspan="3">87.60</td></tr>
<tr><td>Overall OEE (%)</td><td colspan="3">74.15</td><td colspan="3">68.15</td></tr>
</table>

The table shows the results of the simulation run once the change in MMR was applied to the system. No other changes in inputs were applied to the model. As the MMR increased, the OEE has decreased (p-value = 0.00). The resulting decrease in the OEE has also resulted in a decline in the number of units tested. This shows a direct correlation between the two performance measures (Dal et al. 2000). This was affected considerably by one of its components, which is the UPH Efficiency. Given that the workload of the operators has increased by adding another machine that they need to attend to, queueing has become more evident, resulting in more waiting times, considering that the testing process still occurs in a sequential manner. The increase in the MMR also resulted in a longer cycle time. Lastly, there was a significant increase in the operator utilization given that each operator has increased their workload by being assigned to one additional machine.

4.4. Change in the input values

With this model feature, the semiconductor company can opt to change the input values that have been integrated into the model. The following input values that can be changed are listed below:

Duration of operator tasks

- Mean time between failures
- Mean time to repair
- Starting lot sizes

While the model can accommodate the above changes, this study focuses on the duration of operator tasks. Change in MMR often involves analyzing the processes within a system and eliminating non-value-adding ones (Ghosh, 2024). For the case of this study, a sample data set was provided, and the duration of the operator tasks per machine status was reduced. This involves streamlining some of the processes and eliminating non-value-adding tasks. These values were then integrated into the model, along with changing the MMR to 1:6. A simulation run of 20 trials was also performed. A comparison table was then created in which the values between the base model and the new MMR with the applied changes in the operators' tasks. The results were then presented in the table below.

From Table 4, it was shown that changing the duration of operators' tasks affected the performance measures of the model. The resulting values, however, depend on how much time was reduced from the operator tasks. It can be inferred from the results that the changes in the operator activities, coupled with more machine assignments, result in slightly but statistically lower OEE (p-value = 0.00), while output seems maintained (p-value > 0.05). Operational efficiency improved because the operators' tasks were changed, reducing their involvement during equipment uptime activities like SETUP and PACK. Reduced tasks for the operator also mean quicker response. This means that the operator can immediately attend to the machine, given that they can finish their previous tasks more quickly. This leads to reduced queueing, which then leads to reduced waiting times, which could lead to improvement of the UPH efficiency. While improvement in operator times benefited the company, the impact was neutralized with the assignment of more machines to each operator, leading to slightly lower UPH Efficiency and ultimately OEE. Operator utilization also increased given the changes.

Table 4. Comparison table between the base model and an MMR of 1:6 with the applied changes on the operators' tasks.

PERFORMANCE MEASURES	**BASE MODEL**			**MMR of 1:6**		
	Temperature 1	**Temperature 2**	**Temperature 3**	**Temperature 1**	**Temperature 2**	**Temperature 3**
Availability (%)	90.55	85.95	91.50	90.35	85.65	87.60
Operational Efficiency (%)	92	85	87	93.25	86.60	89
Quality Rate (%)	98	98	99	98	98	99
UPH Efficiency (%)	96	91.80	94.90	93.60	86.15	97
OEE (%)	78.85	65.50	74.20	77.40	62.40	74.80
Cycle Time (hours)	33.48	14.63	8.86	33.88	15.60	9.13
Operator Utilization (%)	90.10			93.55		
Total Cycle Time (hours)	56.97			58.60		
Units Tested (in millions)	1.24	1.24	1.22	1.21	1.21	1.21
Overall Availability (%)	89.40			88.50		
Overall Operational Efficiency (%)	89.05			90.60		
Overall Quality Rate (%)	98			98		
Overall UPH Efficiency (%)	94.90			92.10		
Overall OEE (%)	74.15			72.55		

4.5. Deployment of the Simulation Model

While the features of the simulation model are expected to provide the company with very valuable insights, deployment of some features or changes is not without difficulty. This was due to the complexities of the developed model. Improper executions can lead to errors, especially in the part where the results are analyzed. The difficulty level of the different features of the model was ranked depending on their complexity. The ranking was presented in the table below.

Table 5. Difficulty level on implementing the features of the model

FEATURES OF THE MODEL	DIFFICULTY OF IMPLEMENTATION
Monitoring the system across time	1
Change in input values	2
Change in the MMR	3

wherein:
1 = least difficult
3 = most difficult

In changing the input values, adjustments (e.g., task durations, demand changes, and repair times) could be easily made through input tables. The easiest feature to implement was system performance monitoring, as the base model already included the necessary input parameters, predetermined events such as the established yields of each machine temperature, and performance dashboards.

5. Conclusion

Using FlexSim and integrating historical data, a dynamic simulation model was developed for a semiconductor company that captures the operations in its testing area. This tool was then validated and used to analyze the factory's performance using its established MMRs. It also includes important features that the company can use for its analysis. These are especially insightful when testing possible effects of changes in the system. Specifically, benefits can be derived from the ability to monitor the system's performance with respect to time and predict the impact of changes in MMR and input parameters, such as duration of operator times and downtimes. Simulation runs suggest that increasing the number of machines assigned to each operator can lead to decreased OEE and the number of units tested due to the increased workload of the operators. This could then be remedied by analyzing and eliminating possible non-value-adding processes, which could then lead to reduced tasks or routines for the operator.

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Biographies

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Gabriel John L. de Leon is a faculty member of the Industrial Engineering Department at the University of the Philippines Los Baños. He earned a BS Industrial Engineering degree from the same university as the most outstanding student leader recognized with academic excellence, leadership, and service awards. He completed his Master's at De La Salle University, focusing on dynamic waste collection in smart cities. His research interests include vehicle routing and scheduling, website and platform usability, and systems simulation. He is involved in research projects on developing a digital platform to improve and streamline academe-industry linkages. Previously, he served as a Demand Management Planner at San Miguel Pure foods Company, Inc., managing the forecast of retail products and collaborating within the supply chain. He is currently engaged in research as a member of the Circle of Operations Research Enthusiasts (CORE) and in different projects focused on operations research and information systems.

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